ABSTRACT

Title of Dissertation:	EXAMINING THE ENVIRONMENTAL, ECONOMIC, SOCIETAL, AND SUSTAINABILITY POTENTIAL OF SHARED MICROMOBILITY USAGE IN THE U.S.
	Hannah Nicole Younes, Doctor of Philosophy, 2021
Dissertation directed by:	Professor Giovanni Baiocchi, Department of Geographical Sciences

Transportation became the leading sector of carbon dioxide emissions in the United States in 2017 according to the Environmental Protection Agency (EPA). The urgency of reducing emissions from the transportation sector was manifested in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report. Moreover, inequality in income and access to resources continues to increase. From an equity and societal standpoint, transportation modes should be affordable, accessible, and convenient. Developments in technology, communication, and mobile computing have shown great potential in managing resources and increasing efficiency. Innovative research is needed to find ways to reduce such emissions. The following dissertation research focuses on a subset of shared mobility called shared micromobility which include station-based bikeshare (SBBS) and dockless e-scooter and bicycle share (DSS & DBS). The first study establishes a relationship between shared micromobility and public transportation. During three planned transit disruptions, close to 1000 additional bikeshare rides were taken. This finding shows promise that a shift to active, low-carbon mobility is possible. The second study focuses on the temporal determinants and environmental impacts of micromobility. Scooter users tend to be less sensitive to whether conditions than bike users, making scooters more competitive with public transit and auto travel. Moreover, scooter users were more sensitive to gasoline price increases, suggesting a potential shift in auto users in favor of micromobility. The third study examines the access of micromobility in six U.S. cities. In cities with well-established micromobility, higher proportions of minorities and higher poverty rates were associated with fewer trips. The implications for societal equity for this low-carbon mobility are discussed. While micromobility is sustainable and has the potential to compete with more established modes of transportation, like public transit and auto travel, there still remain inequities in access among underserved communities to be addressed.

EXAMINING THE ENVIRONMENTAL, ECONOMIC, SOCIETAL, AND SUSTAINABILITY POTENTIAL OF SHARED MICROMOBILITY USAGE IN THE U.S.

by

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Dedication

To my son, Liam.

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List of Publications

The contents of Chapter 2 were published in the Journal of Transport Geography in 2019 and presented at the 98th Transportation Research Board conference.

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Chapter 1: Introduction

Motivation

The overarching goal of my dissertation, and of my research in general, is to promote sustainability and equity. Growing up in two very different cities – one where public transit was the dominant form of transportation and the other where auto travel was – drove me to question transportation's role in accessibility and sustainability. A memory that ultimately drove my dissertation inquiry was waiting for the bus in Baltimore, back in 2015. A lady next to me lamented that she had missed an important doctor's appointment after waiting one hour for a bus that would never arrive. Most U.S. cities were designed for driving, yet not everyone has access to a car. For those who do not, transportation can serve as a medium for perpetuating income inequality. Job and health-care opportunities can only be as wide as the transportation system provides.

Another important component of my dissertation is to use publicly available data. All of the data used in this research comes from open sources such as the D.C. Department of Transportation; federal agencies such as NOAA, EIA, EPA, and the U.S. Census Bureau; and micromobility vendors such as Lime, Lyft, and Jump. API data are usually not readily available unless local departments make it a requirement that it be public. I find it very important that transportation data be available for research purposes, particularly in places that may be understudied and underserved.

Literature Review

Transportation emissions make up a considerable part of emissions throughout the world and have increased at a faster rate than any other energy-use sector [1]. In 2017, greenhouse gas (GHG) emissions from transportation accounted for about 29% of total U.S. emissions, making it the largest contributor to U.S. emissions [2, 3]. Concurrently, the U.S. are some of the largest emitter of worldwide transportation emissions [1, 4]. Vehicle miles travelled per capita have only recently decreased but still hover around 10,000 miles per person per year [5]; gas prices are too low; cars are larger and heavier and innovations in this sector have been lacking. Funding for public transportation is decreasing, with the quality of public transit decreasing as well.

Meanwhile, the number of electric vehicles has increased since 2013 from less than half a million Electric Vehicles (EVs) to over 5 million EVs globally in 2018 [6-8]. Car emission standards are also becoming stronger and less polluting, although the improvements are not enough to offset increases in total vehicle miles travelled and per capita. New modes of transportation have emerged and become very popular in the last decade, such as Transportation Network Companies (TNCs) (Uber, Lyft, etc.) and shared micromobility, enabling more sustainable travel as compared to driving. The general theme in these new modes of transportation is that they are shared. Shared mobility includes shared cars (e.g., car2go), shared rides (e.g., Lyft, Uber Pool), and shared micromobility (bikes and scooters). Shared mobility is a component of the sharing economy, which is the notion that owning a vehicle will become obsolete and that all modes will be shared.

Researchers suggest that transportation will move towards a sharing economy and fundamentally change the way that we consume things [9]. The sharing economy has the potential to provide a new pathway to sustainability [10]. Indeed, the sharing economy has positive environmental impacts through the reduction in the total resources required (i.e. decreasing the number of motorized vehicle miles traveled) [11]. Moreover, health benefits are provided with the increase in shared cycling services [11, 12]. At the same time, if the sharing economy follows a profit-driven pathway, it is unlikely to drive a transition to sustainability [13]. For instance, bike sharing can actually increase the overall motor vehicle usage if rebalancing and maintenance are not optimized [14]. For the sharing economy to be sustainable, government intervention and monitoring is needed in order to mitigate excessive provision of sharing services [11]. Additionally, the benefits of the sharing economy are not likely to be equally distributed. Disadvantaged and underserved communities have been shown to benefit less from shared mobility services [15].

This dissertation focuses on shared micromobility, which is a subset of the sharing economy. Shared micromobility is an innovative transportation mode that enables users to have access to a low-speed, low-carbon mode of transportation on an as-needed basis. Early documented impacts of shared micromobility include increased mobility, reduced greenhouse gas emissions, decreased automobile use, economic development, and health benefits [16]. In 2010, only 321,000 trips were taken using shared micromobility options, virtually exclusively from station-based pedal bikeshare [17]. By 2017, the annual number of trips had increased to 35 million, with 96% of those trips from station-based bikeshare and 4% from dockless bikeshare. In 2018, over 84 million trips occurred: 45.5 million trips came from those two modes and an additional 38.5 million trips came from dockless e-scooter-share. This impressive increase in e-scooter ridership in just a year shows the potential that shared micromobility can have on mobility overall.

Shared micromobility is expected to reduce the negative externalities of road transport in cities, which is dominated by fossil-fuel powered private car trips [18]. A study showed that, in an overall life cycle assessment (LCA), dockless bikesharing systems in the U.S. emit around half of the CO2 equivalent emissions of personal vehicles [19]. According to surveys, micromobility tends to be dominated by males, high-income, and highly educated individuals [17, 18, 20]. Micromobility is mainly used for short trips and generate higher demand in locations with better transport connectivity and points of interest. Recent surveys and studies have found that up to 45% of micromobility trips replaced car trips [20]. A recent study found that e-scooters could replace 32% of carpool; 13% of bike; and 7.2% of taxi trips [21]. Another survey reported that around 9.3% of dockless scooter trips replaced personal cars [22]. A study found that docked micromobility was preferred for commuting and that docking infrastructure could be vital for making micromobility an attractive alternative to private cars during rush hours [23]. Overall, there is potential for shared micromobility to make up a small, but significant part of travel mode share.

Research Questions and Goals

The research objective of my dissertation is to advance knowledge in the spatial and temporal determinants of usage of shared micromobility. Since 2017, the transport sector is the largest contributor of U.S. greenhouse gas emissions due in majority because of lack of improvement in this sector [24]. Innovative research is needed to find ways to reduce such emissions. Moreover, inequality in income and access to resources continues to increase. From an equity and societal standpoint, transportation modes should be affordable, accessible, and convenient. Development in technology, communication, and mobile computing have shown great potential in managing resources and increasing efficiency. My research focuses on a subset of shared mobility called shared micromobility which includes station-based bikeshare (SBBS), and dockless e-scooter share (DSS).

The first research objective is **to establish a relationship between shared micromobility and public transportation.** I used transit disruptions in Washington D.C. as a tool to analyze how people adapt to using new modes (i.e., bikeshare) when their preferred mode (i.e. metro) is not available. Using data from Capital Bikeshare for the years 2015-2017, I conducted an autoregressive Poisson time series model and found that close to 1,000 additional bikeshare rides were taken during three separate transit disruptions. This finding showed promise that a shift to active, low carbon mobility is possible. The following questions are posed:

- What is the impact of transit disruptions on local bikeshare activity?
- Where did the greatest changes in ridership occur in Washington, D.C.?

The second research objective focuses on **the temporal determinants and environmental impacts of micromobility**. This research compares temporal determinants (weather, weekday, peak times, special events and gasoline prices) between SBBS and DSS and finds some significant differences between the two modes. Namely, DSS users are less sensitive to weather conditions, which is a promising finding that makes DSS more competitive with public transit and auto travel. Additionally, DSS users were more sensitive to gas price increases, suggesting a potential shift in auto users in favor of low-carbon micromobility. The data were collected and processed by the author in real time using publicly available API. In this research, I ask the specific questions:

- What are the temporal determinants of dockless scooter-share use?
- How do the determinants differ from those in station-based bikeshare use?
- Do the two micromobility modes interact together?

The third research objective will use author collected data from 6 different cities to analyze **the relationship between shared micromobility usage and underserved communities**. Ideally, facilitating shared mobility could be used as a way to expand opportunities in low-income communities. In an effort to reduce income inequality and disparities, it is important to understand how low-income and minority residents use these options, whether they improve livelihoods, and what can be done to increase their usage. The results of this study will give recommendations to local officials for curbing negative societal impacts of shared micromobility and promote its accessibility across all users. The following questions are established:

- How do disadvantaged and underserved communities access shared micromobility options?
- Does micromobility improve access for these communities?

The third objective discusses equitable access. Equity can be thought of in two contexts: outcome and opportunity. Equity of opportunity is motivated by the plausibility of treating individuals equally. Equity of outcome requires that individuals have the same share of goods, not merely a chance to obtain them [25]. In this study, I look at equity of outcome. I am not simply interested in whether there are enough scooters available in low-income areas; I measure how much usage occurs in those areas. However, by measuring equity of outcome, I am limited by equity of opportunity; for instance, a recent found that availability of vehicles was inequitable in the Seattle area [26]. This limitation is outlined in the fourth chapter.

Chapter 2: How transit service closures influence bikesharing demand; lessons learned from SafeTrack project in Washington, D.C. metropolitan area.

Abstract

Transportation disruptions offer opportunities to study how people adapt to using new modes of transportation and have important implications for transportation policy and planning. Bikeshare has emerged as a new popular mode of transportation in recent years as it offers a fast, easy, and reliable way to travel short distances, and for its convenience as a first- and last-mile mode to complement transit. It also offers many social, environmental, and health-related benefits and has the potential to promote low-carbon mobility. This study examines changes in bikeshare ridership due to rail transit closures in the Washington, D.C. area and investigates how promoting bikeshare systems in large metropolitan areas could be beneficial in cases of transit disruptions – regardless of the type, cause, and duration. We use disaggregate trip history data to analyze the impact of three different transit closures in 2016 lasting 7 to 25 days. The objective of this paper is to provide insight on how transit disruptions affect bikeshare use. An autoregressive Poisson time series model is used to estimate effects of transit closures on bikeshare activity. Kernel density estimation is applied to understand spatial changes in ridership from a week before, one year before, and after each closure. Results are compared both temporally and spatially and confirm that transit disruptions were associated with increased bikeshare

ridership at the local level. Once the affected Metro stations reopened, bikeshare ridership returned to original levels. We conclude that when within 0.25 mile of a rail station and with a rail station spacing of less than 3 miles, bikeshare can be used as a mechanism for low-carbon mobility to complement transit.

Introduction

Travel disruptions are becoming more commonplace due to the increasing need for maintenance of aging infrastructure, system failures, or natural disasters [27, 28]. Research on travel behavior during a metro system closure has been limited. The majority of the research on transit disruptions focus on day-long transit strikes rather than longer transit service disruptions [27, 29, 30]. Disruptions are important to study because they provide a glimpse at new patterns of behavior that could be adopted [27]. Bikeshare systems offer many potential benefits, such as flexible mobility, reduction in emissions and noise, increase in physical activity, reduced fuel use, and support for multi-modal transportation systems [12]. They could be used as an alternative mode when transit disruptions occur, especially for short commute distances and in cases when a private automobile is not a time- or cost-efficient option. However, very few studies in the past have focused on the relationship between transit disruptions and mode shifts to bikeshare, and thus the relationship between long-term planned transit disruptions and bikeshare ridership is not fully understood. To the authors' knowledge, this study is the first to investigate the effects of planned, long-term transit closures on bikeshare ridership.

In Washington, D.C., 36% of residents report commuting by public transit, 13.7% walk and 4.6% commute by bike [31]. During transit service disruptions, affected travelers may react by adjusting their route, departure time, travel modes, destination, or by cancelling trips [28]. The potential shift towards low-carbon mobility is important to examine. In this study, we are interested in how bikeshare ridership patterns varied during different transit service disruptions. All transit disruptions occurred between 2016 and 2017 and lasted 7 to 42 days. The service changes, known as “SafeTrack”, were part of Washington Metropolitan Area Transit Authority’s (WMATA) long-term project to address Federal Transit Administration (FTA) and National Transportation Safety Board (NTSB) safety recommendations, and to rehabilitate the Metrorail system to improve safety and reliability. The 16 planned disruptions, referred in this paper as *surges*, involved either continuous single-tracking (CST) or closing tracks completely for one week or longer periods. These surges took place across the Washington, D.C. metropolitan area in urban centers and suburban hubs. In this analysis, only the results of surges that involved line segment shutdowns (LSS) – meaning that transit users could not use the rail at all – and had bikeshare available as a viable alternative mode of transportation are presented. Bikeshare is considered an alternative when it is available at two or more consecutive rail stations or two stations not spaced more than three-mile apart (a reasonable distance for biking). Three of the eight closed track surges and two of the eight continuous single-tracking surges qualified for this study, as seen in **Table 1**. An initial analysis indicated that the two continuous single-tracking surges did not have a practically meaningful impact bikeshare trips and thus were excluded from the body of this paper.

We use Capital Bikeshare Trip History data to assess ridership increases in bike use around affected rail stations [32]. This analysis is beneficial in that it uses the entire population using bikeshare rather than a small sample. It overcomes errors associated with sampling and with self-reported survey data. Nonetheless, it has limitations in that there is no information available on bikeshare users in terms of socio-economic characteristics or trip purpose, and it relies on the assumption that if people use a bike from a dock that is within 0.1 mile from a rail station, then they will either use the rail station or use bikeshare as a substitute for transit.

This study contributes to the literature by providing insight on bikeshare behavior during three different time periods in areas of Washington, D.C. that experienced planned transit service disruptions. Transit disruptions are used as an experimental way to observe how bikeshare activity varies if rail transit is no longer an available mode of transportation. Our method accounts for trip-level activity (number of trips between two stations) rather than station-level activity (total number of trips originating from a station). The results provide clear evidence that bikeshare is used as an alternative mode of transportation in times of transit disruptions. This is of significance to policy makers and planners because it indicates that promoting bikeshare systems can be an effective strategy to increase low-carbon mobility.

The remainder of this paper is organized as follows. The next section provides a brief review of the previous literature on transit service disruptions and bikeshare. We then describe the data used in the analysis, followed by an explanation of the two methods used to analyze the data and discussion of the results of our analysis. Finally, the last section provides conclusions, policy implications, and future research directions.

Literature Review

Planned transit disruptions are increasingly common due to aging infrastructure and the increased need for maintenance. Since summer 2017, transit agencies in New York City, San Francisco, Washington, D.C., Boston, and Baltimore in the United States, and Paris and Madrid in Europe, were among those that closed transit stations or track segments for maintenance purposes [33-41]. Unlike strikes or special events, planned transit disruptions due to infrastructure maintenance tend to last longer (days to months) and require travelers to use alternative modes of transportation [42].

Transportation disruptions provide opportunities for transport policy change. Responses to such disruptions provide a window into the range of adaptations that are possible [27, 42]. With the growing urgency for a shift to a low-carbon economy, researchers identify the need for rapid changes to transport policy and travel patterns. Disruptive events make the assumptions around which travel patterns are based more visible. Transport policy changes are characterized as very slow and incremental, in part because of habits in travel behavior [27]. However, disruptive events provide evidence that travelers can easily adapt to abrupt changes and that radical policy changes are possible, if not encouraged.

Bikeshare programs have become considerably popular in cities all around the world and allow users to access bicycles on an as-needed basis. They offer a wide range of benefits, including a reduction in emissions and fuel use, increased physical activity, individual financial savings, and support for multimodal transport connections [43]. As of 2016, over 1,000 cities worldwide had bikesharing programs in place; this trend continues to increase as more cities consider such systems [44-46]. Bikeshare can impact public transit systems by servicing as efficient first- and last-mile connections or as competitors [12], and therefore are considered a viable alternative in the event of transit disruptions (especially planned system closures).

Despite the potential of bikeshare systems as an alternative travel mode in cases of transit service disruptions, most research on transit disruptions effects has focused on their impact on highway congestion or modal switches to motorized vehicles [47, 48] and neglected the changes in bikeshare ridership (if available). A few studies have investigated the impact of planned transit closures due to infrastructure maintenance on mode choice, using stated and revealed preference panel surveys [28, 49]. Pnevmatikou (2015) did not consider biking as a mode due to low ridership in their area of study (Athens, Greece).

Zhu et al. (2017) studied the same transit disruption as in this paper but focused on behavioral reactions to transit services changes (modal switch, trip cancellation, changing departure time), and collected trip purpose information and socio-economic variables. They focused on the first two surges that occurred (Surges 1 and 2), while this paper focuses on surges that involve system closures and had Capital Bikeshare available as an alternative mode (Surges 2, 4, and 10). Therefore, there was an interesting overlap for Surge 2. They found that most affected surveyed travelers were commuters (82%), were frequent Metro users (75% used Metro at least

5 days a week), mostly male (61%), and had a bachelor's degree or higher (72%). Forty percent of the sampled population indicated that they planned to switch modes during the surge. No strong conclusion was made with respect to biking because the survey did not differentiate between walking and biking, likely because non-motorized transportation in Washington, D.C. makes up a small portion of mode share.

To the best of the authors' knowledge, to date, there are only three other studies that examine the impact of public transit disruption on bikeshare [29, 50, 51]. The first two studies investigate the impact of separate London Transit strikes on bikeshare use. Fuller et al. (2012) found that the disruption resulted in a statistically significant increase in total number of bicycle trips per day. Similarly, Saberi et al. (2018) found that bikeshare ridership increases during a time of disruption by up to 88%. The latter study was published after the initial submission of this paper and analyzes how the introduction of Single Trip Fare (STF) and transit disruptions impacted bikeshare ridership and revenue in Washington, D.C. using very different approaches than in this present study.

Our study differs from Fuller et al. (2012) and Saberi et al. (2018) in that we explore the effects of three different planned public transit disruptions that lasted 7 to 25 days rather than a single day, and that took place during various seasons in 2016 and 2017. Moreover, the nature of the disruptions differs in that the strike impacted the entire London Tube while the maintenance impacted only segments of Washington, D.C.'s Metro. We do not expect network-wide changes in bikeshare ridership due to the disruptions, but rather spatially local changes near the affected

Metro areas. Kaviti et al. (2018) analyzed the impact of pricing and transit disruptions on SafeTrack surges 1 through 9 using a paired t-test simple linear regression and ridership. They did not differentiate between closed stations and single tracking disruptions. They found that the introduction of the Single Trip Fare (STF) positively impacted bikeshare trips. However, they did not control for the presence of surges in their regression model. They separately analyzed the effect of the surges on ridership using week long periods before, during and after each surge and controlled for adverse weather events by removing observations that experienced precipitation and by considering weekdays only [51].

Data

This study utilizes historic bikeshare ridership data available publicly in the study area, which includes information such as date and time of trip, trip duration, trip start/end locations, and membership status of the user for all bikeshare trips (see **Figure 2a**). This data was accessed and downloaded from the Capital Bikeshare website for various time periods before, during, and after each SafeTrack project period. This source is comprehensive, but it does not provide any information about station capacity restraints, sociodemographic information about the users of the bikes, or information on trip purpose. We rely on the assumption that trips to rail stations are associated with Metro ridership (either replacing Metro trips or complementing for closures).

We focus on three areas during three different periods. Surge 2 occurred in June 2016 and lasted 16 days (**Table 1**). It took place in a mostly residential area in southeast Washington, D.C., close to the U.S. Capitol. Stadium Armory and Potomac

Avenue stations were completely closed and the nearest open station going into the city center was Eastern Market. Surge 4 occurred in July 2016 and lasted 7 days. Crystal City Metro station was completely shut down and the nearest station going towards the city center was Pentagon City Metro station. It took place in a mixed-use neighborhood of Northern Virginia in the Pentagon area. Surge 10 occurred in November 2016 and lasted 25 days. Brookland CUA and Rhode Island Metro stations were completely closed and the nearest opened station going towards downtown Washington, D.C. was the New York Avenue (NoMa) station. Transfer point Fort Totten station was the nearest opened station to the north of Brookland-CUA Metro station (**Figure 1**). Surge 10 spanned several mixed-use areas of Washington, D.C., from the busy Union Station at the south to a relatively residential area at the north.

Table 1: Description of SafeTrack Surges

Surge Number	Date	Duration	Lines	Impact	Area Affected	Closed Stations Impacted	Bikeshare Available at both stations? (within .1 mile)	Biking Distance
1	June 4 – 16, 2016	13 days	Orange Line Silver Line	CST	East Falls Church to Ballston	East Falls Church to Ballston:	Yes	3.0 mi
2*	June 18 - July 3, 2016	16 days	Orange Line Blue Line Silver Line	LSS	Eastern Market to Minnesota Ave & Benning Road	Minnesota to Stadium Armory:	No	3.5 mi.
						Stadium Armory to Potomac Ave:	No	1 mi.
						Potomac Ave to Eastern Market Station:	Yes	0.7 mi
3	July 5 - 11, 2016	7 days	Yellow Line Blue Line	LSS	National Airport to Braddock Road	National Airport to Braddock Road:	No	3.8 mi
4	July 12 - 18, 2016	7 days	Yellow Line Blue Line	LSS	Pentagon City to National Airport	National Airport to Crystal City:	No	1.3 mi.
						Crystal City to Pentagon City:	Yes	0.8 mi
5	July 20 - 31, 2016	12 days	Orange Line Silver Line	CST	East Falls Church to Ballston	*See Surge 1*		
6*	August 1 - 7, 2016	7 days	Red Line	CST	Takoma to	Takoma to Silver Spring:	Yes	1.8 mi

					Silver Spring			
7	August 9 - 21, 2016	13 days	Red Line	CST	Shady Grove to Twinbrook	Shady Grove to Rockville:	Yes	4.1 mi.
						Rockville to Twinbrook:	No	2.5 mi.
8	August 27 - September 11, 2016	16 days	Yellow Line Blue Line	CST	Franconia-Springfield to Van Dorn Street	Franconia-Springfield to Van Dorn Street	No	4.3 mi.
9	September 15 - October 26, 2016	42 days	Orange Line	CST	Vienna to West Falls Church	Vienna to Dunn Loring-Merrifield	No	3.7 mi.
						Dunn Loring-Merrifield to Falls Church	No	3.4 mi.
10*	October 29 - November 22, 2016	25 days	Red Line	LSS	Fort Totten to NoMa	Fort Totten to Brookland CUA:	Yes	2.3 mi.
						Brookland CUA to Rhode Island Ave:	Yes	1.0 mi.
						Rhode Island Ave to Noma:	Yes	1.3 mi.
11	November 28 - December 20, 2016	23 days	Orange Line Silver Line	CST	East Falls Church to West Falls Church	East Falls Church to West Falls Church:	No	2.6 mi.
12	February 11 - 28, 2017	18 days	Blue Line	LSS	Rosslyn to Pentagon	Rosslyn to Arlington Cemetery:	No	2.3 mi.
						Arlington Cemetery to Pentagon:	No	2.2 mi.
						Rosslyn to Pentagon:	No	3.5 mi.
13	March 4 - April 12, 2017	40 days	Blue Line Yellow Line	CST	Braddock Rd to Huntington/Van Dorn St	Huntington to Eisenhower Avenue	No	1.4 mi.
						Eisenhower Avenue to King Street	Yes	1.1 mi.
						King Street to Braddock Road	Yes	0.9 mi.
14	April 15-May 14, 2017	30 days	Green Line	LSS	Greenbelt to College Park	Greenbelt to College Park:	No	
15*	May 16 - June 15, 2017	31 days	Orange Line	LSS	New Carrollton to Stadium-Armory	*See Surge 2*		
16	June 17 – 25, 2017	9 days	Red Line	LSS	Shady Grove to Twinbrook	*See Surge 7*		

('*' indicates that at least one impacted station is inside the D.C. boundaries)

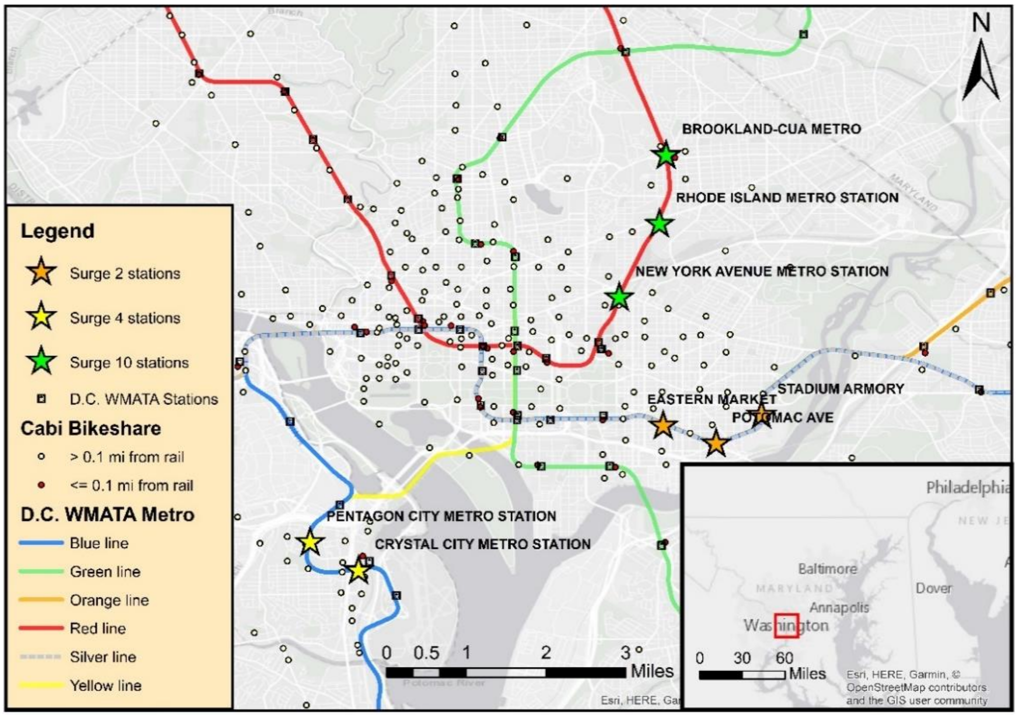


Figure 1: Map of study area

The time series analysis uses locally specific data for the entire time period. All trips with origins and destinations within 0.5 mile of each affected station are aggregated to daily level. Daily trips are further broken down by the percentage of casual and registered users and by the percentage of morning peak, mid-day, evening peak and night trips. The three dependent variables are the daily bikeshare activity for transit stations within 0.5 mile of affected transit stations for surges 2, 4, and 10. Weather variables used as controls are obtained from the National Oceanic and Atmospheric Administration [52]. The kernel density estimation analysis uses the entire spatial extent of bikeshare usage and temporally specific periods before, during and after each surge. The data are aggregated to origin-destination to capture directionality in trips. Seasonality is assumed to be constant spatially. Weekends are excluded from the kernel density estimation because bikeshare usage varies considerably spatially, as is shown in the results of the forthcoming time series analysis and complemented by the survey results of Zhu et al. (2017). The methodology is outlined in the following section.

Trip ID	Time	Start Station ID	End Station ID	Rider Type
1	1/1/2016 8:35	29	78	Casual
2	1/1/2016 11:20	100	21	Member
3	1/2/2016 6:02	29	78	Member
4	1/2/2016 12:27	100	19	Member
5	1/3/2016 1:45	100	19	Casual

a)

Date	Trip Count (Subset: Trip pairs within 0.5 mi of Surge X)	% Casual Riders	% Peak hour riders
1/1/16	2	50%	50%
1/2/16	2	0%	50%
1/3/16	1	100%	0%
1/4/16	...	...	...

b)

Station Pair	Trip Count (Subset: 1/1-1/2/2016)
29-78	2
100-21	1
100-19	1

c)

Figure 2: Description of bikeshare data structure. (a) Raw trip level data: each individual trip has its own row. Data contains information on trip duration, time and date, membership type, bike number, etc. (b) Time-series data: each date has its own row and trip count is aggregated. Some information is preserved by introducing percentages of membership type and time of usage and mean duration of trip. In this study, we subset trips within a certain radius of each surge. (c) Origin-destination or station pair level data: each station pair has its own row and a new column is created with the number of trips taken per pair. In this study, we subset trips within a certain time frame. Unlike station level data, directionality of trip is preserved.

Methodology

The main research objectives in this analysis are (1) to measure and quantify the impact of transit disruptions on local bikeshare and (2) to detect where the greatest changes in ridership occur spatially. We use an autoregressive Poisson log-level time series model to address the first question and kernel density estimation (KDE) to address the second. The two methods constitute of comparisons between temporal and spatial scales (surge-specific and network-wide).

Local trip-level time series analysis

A time series analysis is conducted to assess the statistical and policy significance of disruptions on bikesharing trips at the local scale. The dependent variable is daily trip count between bikeshare stations within 0.5 mi of affected areas from January 1st, 2015 to December 31st, 2017. The ordinary linear model is not appropriate with this data because the response variable assumes discrete values [53]. The autocorrelation function indicates that time dependency in trips indeed exists (see supplemental material for plots of autocorrelation functions in dependent variables). Daily bikeshare trips, as is often the case with count series data, are not normally distributed and is assumed to follow a Poisson distribution. Based on the nature of the problem and the characteristics of the data, the most suitable model is an autoregressive Poisson model for count time series specified by Liboschik et al. (2017). The conditional mean of the model is linked to its past values and past observations and to potential covariates effects and its conditional distribution is Poisson [53-55]. The model is specified as log-level. We use three autoregressive terms: 1-day lag, 1-week lag, and 1-year lag to capture both short-term and long-term effects. Seasonal fluctuations are controlled for using weather related variables suggested by Gebhart & Noland (2014). Moreover, we control for non-work day fluctuations using dummy variables [56]. The last predictor is the intervention variable indicating the presence of the surge.

We are further interested in understanding the nature of each increase. A simple linear regression is used to analyze changes in proportion of casual users and in peak hour usage during each surge (controlling for non-workdays and weather variables). A log-level Poisson model is used to analyze changes in trip ridership for weekend and weekday separately. This analysis is done for all trips within 0.5 mi of each surge, similarly to the main time series analysis.

Spatio-temporal Comparison using Kernel Density Estimation

The purpose of this analysis is to visualize changes in ridership due to a planned long-term transit disruption. The main questions asked are where did the greatest concentration of trip increases occur and what is their extent. Kernel density estimation is conducted to detect unusual or atypical increases in bike usage during the surge period. Unusual bike usage refers to trips that are unexpected if there were no surge period. KDE is a non-parametric way to estimate the probability density function of a random variable. KDE is commonly used in transportation research to estimate activity space of individuals [57, 58] and to estimate probability density of vehicle crash [59-61]. Peer-reviewed studies that apply KDE methods using bikeshare data are limited. Chen et al. (2015) used Washington, D.C. bikeshare data from 2012 to 2014 to identify urban activity centers using KDE. In their study, they use station-level activity (number of bikes leaving and arriving to a particular station during a particular time period) and found that such bikeshare data can successfully identify urban activity centers [62].

Unlike previous studies, we use origin-destination level activity instead of station-level activity. The number of origin-destination trip combinations taken during a particular period was calculated. Capital Bikeshare has 440 stations, so the total number of origin destination combinations would be 440^2. This is of course much higher than what is observed in reality, which is closer to about 10-20% of those trip combinations. Each trip combination has an attribute (trip count) that designates the number of times a trip was taken for a particular time period. While KDE works on both point (e.g., stations) and polyline (trips in **Figure 2c**) data, we chose not to aggregate the data to station level for the following two reasons. First, the surges were local to a few transit stations in a network of 91 rail stations. Second, the nature of the transit disruption is such that it impacted people living along linear track segments (one or more stations in a row). Therefore, we expect trips from the same station to decrease in one direction and to increase in another. To capture the direction and magnitude of trips, one must use origin-destination data, as all this information would be lost in station-level data. For each surge, the change in number of trips for three time periods was calculated: the days preceding the surge, the same time period one year earlier (2015), and the same time period one year later (2017).

KDE on its own estimates the probability density of station-pair combinations that increased during a surge. Each trip combination is assigned a weight based on how much ridership increased during the surge. This weight is simply defined as the squared change in ridership. We squared the change in ridership in order to emphasize significant increases in activity. The limitation with such a measure is that trips that increased from 20 to 40 were weighted less strongly than popular trips that increased from 200 to 250. Nonetheless, this method was useful in capturing increases in bikeshare ridership close to each surge area, as outlined in the results.

Analysis and Results

Washington, D.C.'s Capital Bikeshare trips increased on average 9% annually from 2015 to 2017 (**Figure 3**). **Table 2** outlines daily average number of trips for all capital bikeshare trips and for bikeshare trips within 0.5 mi of each surge one year before, one week before, during, one week after, and one year after each surge. We use average number of daily trips because of differences in surge lengths (varying from 5 weekdays to 15 weekdays). Weekend trips are excluded from this table because of their varying spatial dynamics. All trips, local and network-wide, increased from 2015 to 2017. The average number of trips during the surge is shows a clear increase during the surge for activity within 0.5 mi of each surge but not for the entire bikeshare network. Average number of trips shortly before and after each surge remain relatively constant, hinting that the surges did not have a lasting impact on bikeshare ridership. **Figure 4** displays a visual of non-adjusted daily trips for the times shortly before and after each surge. One can observe that trips appear to return to original numbers after transit disruptions end.

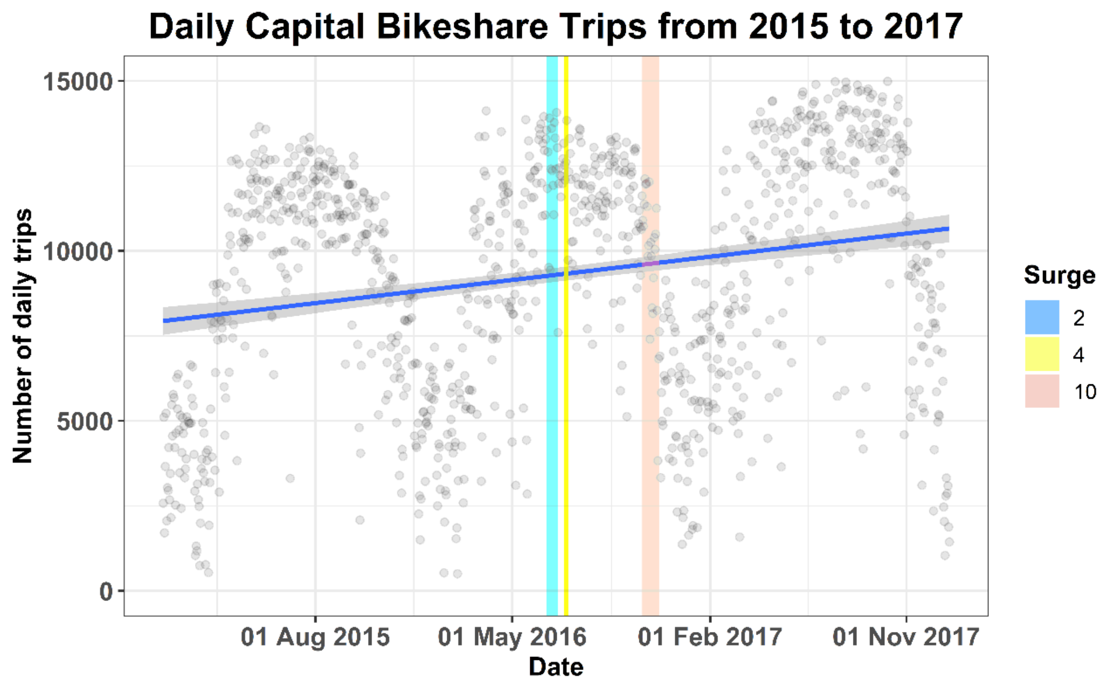


Figure 3: Daily number of trips from January 2015 to December 2017. Notice the prominent seasonal fluctuations and the growing trend in the three-year period in Washington D.C.

Table 2: Description of bikeshare activity for Surges 2, 4 & 10

	Surge 2		Surge 4		Surge 10	
Pre-Surge Time period (Weekdays)	6/2-6/17/2016		7/5-7/11/2016		10/6-10/28/2016	
Surge Time Period	6/18-7/4/2016		7/12-7/18/2016		10/29-11/22/2016	
Post-Surge Time period (Weekdays)	7/5-7/18/2016		7/19-7/25/2016		11/23-12/15/2016	
Total Length of Surge in days	16		7		25	
Length of Surge in Weekdays	10		5		15	
	Stations within 0.5 mi	All Stations	Stations within 0.5 mi	All Stations	Stations within 0.5 mi	All Stations
Total Number of Weekday Trips during Surge	758	118,572	892	60,116	1303	151,812

Average number of weekday trips 1 year before surge	58.6	11,454	131	11,957	47.4	9,187
Average number of weekday trips before surge	44.8	12,407	126	12,185	59.9	11,648
Average number of weekday trips during Surge	75.8	11,857	178	12,023	86.9	10,121
Average number of weekday trips after surge	49.3	12,104	129	12,173	43	7,058
Average number of weekday trips one year after surge	60.2	13,708	149	12,376	51.2	9,687

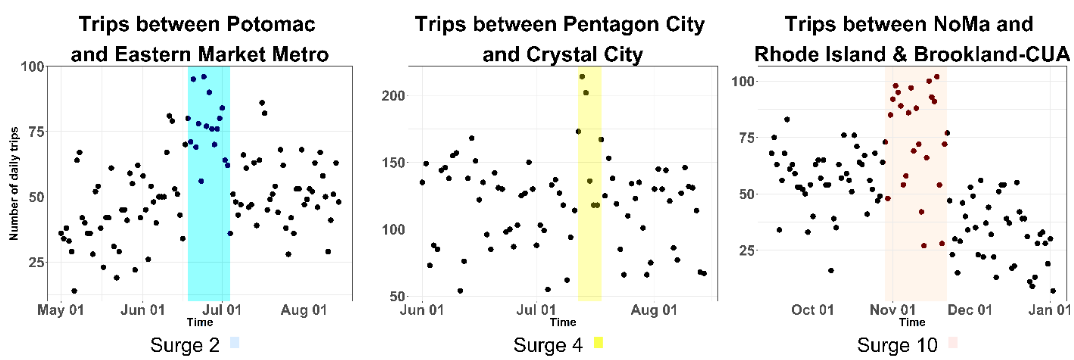


Figure 4: Non-adjusted weekday ridership between bikeshare stations within 0.50 mi of disrupted Metro stations before, during (as shaded), and after Surges 2, 4 & 10 in 2016.

Local Trip-Level Time Series Analysis

We capture the effect of each surge by detrending and de-seasonalizing locally specific data using a regression. Temperature, maximum wind speed, and visibility were used to control for seasonality. Precipitation was excluded from this analysis because of its very low correlation with daily bikeshare trips. Dummy variables are used to control for non-workdays (weekends and holidays) and non-school days (mid-

June to end of August). A dummy variable indicating the presence of each surge is used as the intervention variable.

The results of the Poisson model and autoregressive Poisson model for each surge are presented in **Table 3**. We find that the Poisson model with autoregressive terms performs better than the traditional Poisson model for each of the surges when using the AIC and log-likelihood coefficients. Moreover, the autoregressive Poisson model does better at reducing autocorrelation in the residuals (refer to supplementary material for autocorrelation function plots of model residuals). The time lags are all significant, confirming the dependent nature of bikeshare data on past observations. Temperature and visibility have a positive and significant effect and windspeed has a negative and significant effect on bikesharing trips. These weather effects are in line with the literature [56, 63, 64]. Non-working days have locally specific impacts. For surges 4 (Pentagon area) and 10 (downtown Washington, D.C.), weekends and holidays see fewer activity. Surge 2, which took place in a more residential sector of the District of Columbia, actually sees an increase in trips during weekends and holidays. Since non-working days have spatially different impacts on the region, they are excluded from the KDE analysis, which requires variables to be spatially constant. The summer dummy variable, which accounts for non-school days, negatively impacts bikeshare activity in the surge areas. None of the areas are strong tourist attractions so these results make sense. Controlling for the introduction of the Single Trip Fare (STF) in June 2016 does not significantly improve the model for any of the surges and is therefore excluded from the final models. Finally, the intervention variable, which is specified by the dates in **Table 1**, is statistically significant and positive for all three respective surges. We now look at the practical significance of the results.

Table 3: Results of Time Series Analysis for Surges 2, 4 & 10

	Poisson			Poisson with Autoregressive terms		
Coefficients (β)	Surge 2	Surge 4	Surge 10	Surge 2	Surge 4	Surge 10
Intercept	1.898 *** (0.06)	2.397 *** (0.04)	1.797 *** (0.06)	1.18 *** (0.07)	1.52 *** (0.05)	1.05 *** (0.07)
1-day lag	N/A	N/A	N/A	0.21 *** (0.014)	0.20 *** (0.008)	0.21 *** (0.01)
1-week lag	N/A	N/A	N/A	0.098 *** (0.012)	0.087 *** (0.008)	0.092 *** (0.01)
1-year lag	N/A	N/A	N/A	-0.010 *** (0.004)	0.009 *** (0.003)	0.04 *** (0.004)
Presence of Surge	0.302 *** (0.03)	0.258 *** (0.03)	0.573 *** (0.024)	0.22 *** (0.03)	0.217 *** (0.03)	0.372 *** (0.025)
Temperature	0.016 *** (0.0003)	0.017 *** (0.0002)	0.015 *** (0.0003)	0.010 *** (0.0004)	0.013 *** (0.0003)	0.0096 *** (0.0004)
Wind Speed	-0.009 *** (0.0009)	-0.008 *** (0.0007)	-0.009 *** (0.0009)	-0.008 *** (0.0009)	-0.006 *** (0.0007)	-0.008 *** (0.0009)
Visibility	0.107 *** (0.006)	0.14 *** (0.004)	0.14 *** (0.006)	0.094 *** (0.006)	0.119 *** (0.004)	0.113 *** (0.006)
Weekends/Holidays	0.194 *** (0.009)	-0.58 *** (0.008)	-0.26 *** (0.010)	0.15 *** (0.010)	-0.473 *** (0.010)	-0.204 *** (0.011)
Summer	-0.076 *** (0.013)	-0.094 *** (0.009)	-0.115 *** (0.013)	-0.055 *** (0.013)	-0.067 *** (0.009)	-0.077 *** (0.013)
AIC	9945	14066	10324	9572.5	13459	9682
Log Likelihood	-4965	-7026	-5155	-4776	-6719	-4831

(***) indicates significance at 0.01 level.

The models are specified as log-linked and the coefficients β in **Table 3** for the Poisson Autoregressive model are converted to percentages in **Table 4** using the following formula [65, 66]:

$$\%\Delta y = 100 * (e^{\beta} - 1)$$

For a one-unit change in independent variable *x*, we expect the relative change in *y* to be the exponent of the coefficient of *x* minus one multiplied by one hundred percent. The transit disruptions (presence of surge) lead to between 24% and 45% more trips in bikeshare stations within 0.5 mile of each surge. This amounts to about 11, 22 and 21 additional daily trips around surges 2, 4, and 10, respectively, compared to average daily ridership during the three-year span. While this may not appear substantial, one must consider that bikeshare activity is dependent on bikeshare station capacity [67]. Given that the transit stations often have one bikeshare station with 15-20 racks, some of which should always remain empty so that people can return bikes easily, the magnitude of bikeshare trips is limited by this important factor. We estimate that a combined 856 additional trips were taken between stations within 0.5 mile of each affected area. This number is likely to be higher if one accounts for changes in bikeshare activity due to the slowdown of the transit system throughout the region.

Table 4: Interpretation of coefficients as percentage of change in the mean of y for a one-unit change in x.

	Surge 2	Surge 4	Surge 10
Presence of Surge	24.21%	24.18%	45.14%
Temperature	1.05%	1.17%	0.96%
Wind Speed	-0.77%	-0.64%	-0.79%
Visibility	9.89%	12.70%	12.0%
Weekends/Holidays	16.29%	-37.71%	-18.48%
Summer	-5.32%	-6.46%	-7.41%

While trips significantly increased during the surge, there is interest in understanding the nature such increase. We performed regressions for trips within 0.5

mi of each surge and tested the impact of the disruptions on the proportion of casual users (non-registered users), the proportion of trips taking place during peak hours (which we defined as starting between 6 am and 9 am and 3 pm and 6 pm), and weekend versus weekday only trips. We used a generalized linear regression for the first two proportion variables and a log-linear Poisson model for the latter two count variables and controlled for weather and non-working days (as applicable). Proportion of casual users increased around surges 2 and 10, indicating a possibility of increased ridership from new groups. Surges 2 and 10 spanned two weeks or longer, perhaps giving more possibility for increases in casual ridership than surge 4, which lasted only one week. Surge 10 was associated with statistically significant increases in the proportion of peak hour users; however, no conclusion can be drawn with respect to the other two surges. Weekend activity increased, albeit to a lesser extent than weekday activity for surge 10 and did not statistically significantly increase in the surge 2 area. Weekend activity for surge 4 is significant but one should note that only one weekend occurred in that period. Finally, weekday trips mirror the results of the Poisson model in **Table 3**, with slightly larger coefficients, indicating that the greatest growth came from weekday trips across all surges.

Table 5: Impact (β) of presence of surge on selected variables

Dependent variable	Surge 2 (16 days)	Surge 4 (7 days)	Surge 10 (25 days)
% of casual users	0.06 ($p = 0.0002$) ***	0.06 ($p = 0.12$)	0.11 ($p < 0.0001$) ***
% of peak hour users	0.04 ($p = 0.14$)	-0.01 ($p = 0.76$)	0.10 ($p < 0.0001$) ***
Weekend only (log)	0.16 ($p = 0.84$)	0.24 ($p = 0.0002$) ***	0.38 ($p < 0.0001$) ***
Weekday only (log)	0.42 ($p < 0.0001$) ***	0.26 ($p < 0.0001$) ***	0.62 ($p < 0.0001$) ***

(***) *indicates significance at 0.01 level. N = 1096 for first two variables; N = 314 for Weekend only; N = 782 for Weekday only.*

Kernel Density Estimation

Kernel density estimation is used in this paper estimate the spatial distribution of increases in trip ridership. In our case, we use 10, 5, and 15 weekdays for Surges 2, 4, and 10, respectively, and compare with the same time duration before the surge (pre-surge), and one year before and after the surge (full results available in the Supplementary Material). Results from the time series analysis indicate that trips within 0.50 mi of each surge increased significantly. Without applying KDE, it is still unclear how the increases in trips nearest to the surge compare to other increases in the rest of the network. Surge 2, for example, happened at a time when tourist activity increases and saw a large increase in trips around the National Mall, a popular tourist attraction. To minimize single period temporal effects, we use Raster Cell Statistics in ArcGIS to sum the combined kernel density estimates of all time periods and consistently find that the surge areas display the highest increases in trips, exceeding visually the densities of tourism increases (**Figure 5**).

The highest distribution of increases in trips occurs nearest to the first opened stations in the direction of the downtown city center (New York Ave, Eastern Market and Pentagon City) and disperses in the direction of the closed transit stations. Because of this directionality, it appears that travelers close to the disruptions temporarily used bikeshare as a way to reach unaffected nearby transit stations rather than as a substitute for a full transit trip. Future research is suggested to formally test this asymmetric flow. Transit closures impacted the rest of the network by slowing down service and leading to overcrowding on unimpacted transit lines. However, based on this analysis, the effects of the surge on bikeshare activity beyond the 0.5 mi radius are not evident. We observe moderate increases in trips in the city center for all surges. Yet, we refrain from attributing network wide changes in bikeshare ridership to the surges due to the spatially and temporally variant nature of the network-wide data.

An important takeaway is that stations in close proximity of Surges 2, 4, and 10 all display atypical increases in bikeshare ridership. The changes are not only atypical, they are the greatest changes in bikeshare ridership out of the entire network, exceeding ridership changes from weekday touristic activity. The surges have a considerable impact on bikeshare ridership trip pairs, more so than what is seen with total station activity. This is important to consider because the origin-destination data (station pairs) that provide direction and magnitude of trips (in length) were found to be non-trivial factors in this analysis.

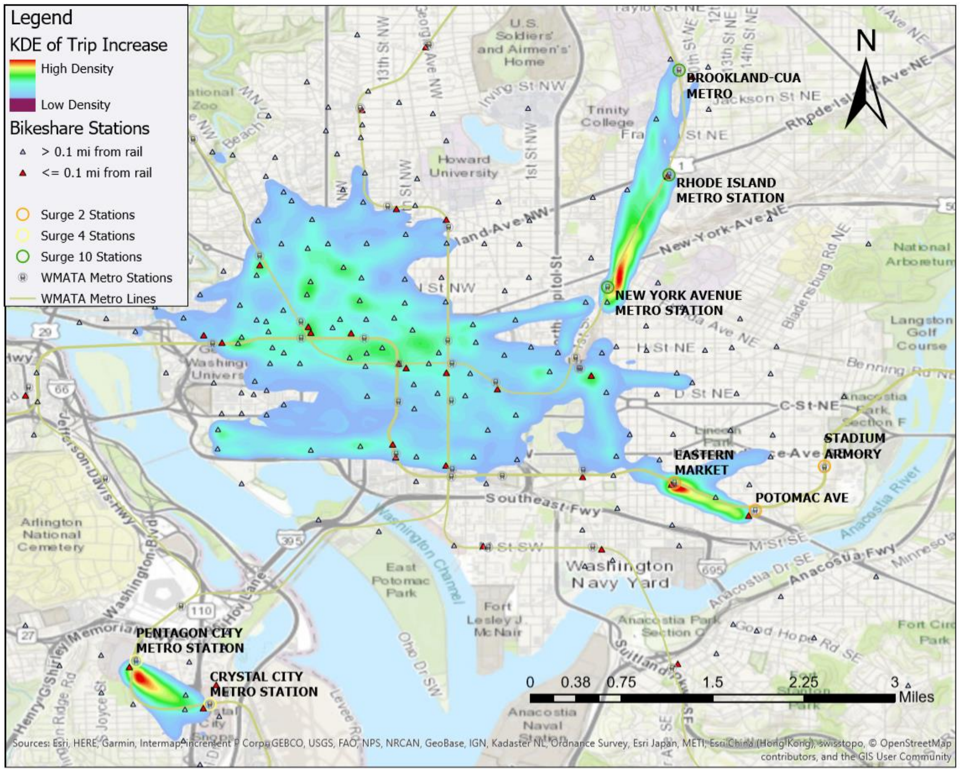


Figure 5: KDE visualization of ridership increases during surge time periods (combined for surges 2, 4, and 10) when compared to pre-surge time 2016, same time period in 2015, and same time period in 2017. Estimates in the bottom quintile are excluded in order.

Conclusion

This study sought to explore the effects of three public transit disruptions in Washington, D.C. during the SafeTrack project on bikeshare demand. The SafeTrack project took place from June 2016 to June 2017 through 16 different surges. Initial testing suggested that the slowdown caused by single tracking surges did not meaningfully impact trips within 0.5 mi of affected areas and thus were excluded from the main analysis. Surges 2, 4, and 10 qualified for this analysis as they consisted of the track closure that affected two or more stations, had bikeshare available within a reasonable distance of each affected Metro station, and had acceptable first- and last-mile biking distances between rail stations.

Our analysis overall suggests that the transit station closures had a considerable effect on bikeshare ridership. The increase in bikeshare traffic between closed and opened rail stations and the results of the KDE visualization indicate that it is likely that bikeshare was used as first- and last-mile solutions rather than as a substitute for transit. This is an important finding as it furthers understanding of interactions between modes during transit disruptions. Surges that required bike users to bike distances longer than 2.5 miles did not see considerable increases in ridership. At that point, travelers likely reverted to motorized modes such as bus or private car. Weekday ridership increased more than weekend ridership, which indicates a possibility of commuters rather than leisure trips. Registered users make up on average around 80-90% of all bikeshare users in Washington, D.C., but there was an interest in understanding whether the proportion of casual users increased during the surge. While increases in proportion of casual users were significant for surges 2 and 10, one should be careful in interpreting these results as surges may have attracted new riders who became registered users because of the surge and thus would not be captured in the casual user proportion. More analysis is needed to understand the nature of increases in bikeshare ridership during transit disruptions. A time-of-day and day-of-week analysis showed that most of the increase in ridership occurred during weekdays for all surges while peak hour usage increased significantly for surge 10 but not for the others. These differences between surges are not surprising given that surge 10 lasted nearly one month and spanned a busier and wider area of Washington D.C. than the other surges. Bikeshare ridership in the affected areas appeared to return their pre-surge stage after each surge, suggesting that the disruptions did not have a lasting effect on bikeshare ridership.

Conclusively, transit disruptions provide a unique opportunity to understand alternatives for transit riders and how travel decisions are made, both of which are crucial for drafting future transportation policies [42]. Promoting bikeshare can be used as a strategy to increase or promote low-carbon mobility in Washington, D.C. Policy and planning recommendations for bikeshare management are to (1) consider bikeshare station capacity during a transit disruption. Station capacity is much lower than the number of people who have to switch modes because of transit disruptions. Because bikeshare activity is limited by station capacity, planners should consider this when providing alternative modes for transit riders; (2) account for proximity of rail and bikeshare stations - several surges did not qualify for this study because bikeshare was further than 0.25 mile from a station and we considered that to be too far to be a viable alternative to transit; and (3) examine rail station spacing - some stations had bikeshare available at both stations, but the rail spacing exceeded 3 miles. This is more complicated because rail transit spacing is established infrastructure that cannot be cheaply or quickly altered. One recommendation is to provide bikeshare stations between two consecutive rail stations to allow people who live or work between two stations to use bikeshare as a complementing option.

Future research could focus on complementing this type of analysis with surveys to confirm the trip purpose of bikeshare users and understand the attitudinal preferences towards modal shift to bikeshare during transit disruptions, as well as its underlying reasons. This would help planners and policy makers expand and improve bikeshare systems in large metropolitan areas and to promote bikeshare ridership as it provides information on whether planned transit disruption attracts new bikeshare users. It would also be interesting to apply this type of analysis to other cities possessing bikeshare that have experienced or are planning for a planned transit disruption in the future, to better understand how travelers respond.

Chapter 3: Comparing the Temporal Determinants of Dockless Scooter-Share and Station-Based Bikeshare in Washington D.C.

Abstract

Dockless, or free-floating mobility has gained unprecedented popularity in the last year, from being virtually non-existent in 2017 to facilitating over 38.5 million trips in 2018. Hitherto, few studies have analyzed dockless micromobility, and scooter-share particularly using big data. This paper analyzes and compares the determinants of dockless scooters-share (DSS) and of station-based bike-share (SBBS) rides in D.C. It made use of API data from dockless vendors and historical trip data from Capital Bikeshare from December 2018 to June 2019. Two variables were estimated: hourly number of trips and hourly median duration of trips. A negative-binomial regression model was performed at the hourly scale controlling for environmental and economic variables including weather-related data, gasoline prices, local events or disturbances, day of week, and time of day. Four groups were analyzed: all of micromobility combined and weighed, SBBS members, SBBS non-members, and DSS. Three important findings emerged: (1) Temporal use differences between the three user groups were found, but DSS users behave most similarly to SBBS non-members. (2) Weather is less of a disutility for DSS users than for SBBS users. We attribute this to the physical ease of using a scooter and to the convenience of ending a trip at the actual destination rather than a nearby docking station. (3) All micromobility user types are sensitive to changing gas prices, although DSS users appear slightly more sensitive both in terms of trip count and duration. Additionally,

an analysis of the interaction between modes found a possible competition between DSS and SBBS non-members and a complementary relationship between DSS and SBBS members. We conclude that significant differences exist between the two modes, and combined with its sudden and rising popularity, micromobility and DSS in particular could have a major role in promoting a shift towards low-carbon mobility.

Introduction

Dockless micromobility, and in particular e-scooter-share (DSS) has emerged as an attractive mode of transportation in recent months. Bike-sharing systems have been an important part of the sharing economy for the last decade and until recently, were station-based. Dockless, or free-floating bicycles arose in 2016 and gained some popularity due to their flexibility and convenience [17]. It wasn't until 2018 that e-scooters and e-bikes became prominent in many U.S. cities, overtaking pedal bikes as the preferred micromobility vehicle [17]. That same year, dockless scooters made up 38.5 million scooter trips, dockless bikes 9 million, and station-based bikes 36.5 million. **Figure 6** displays the recent trend in shared micromobility in the U.S. since 2010. Micromobility has been experiencing a steady increase in trips. In 2018, however, the number of trips more than doubled from the previous year, with most of the added growth coming from dockless scooters [17]. By the end of 2018, there were over 85,000 e-scooters available for public use in the U.S. Dockless e-scooters are a more attractive option compared to conventional bikes in that they require considerably less physical effort and are more convenient to ride than docked bicycles.

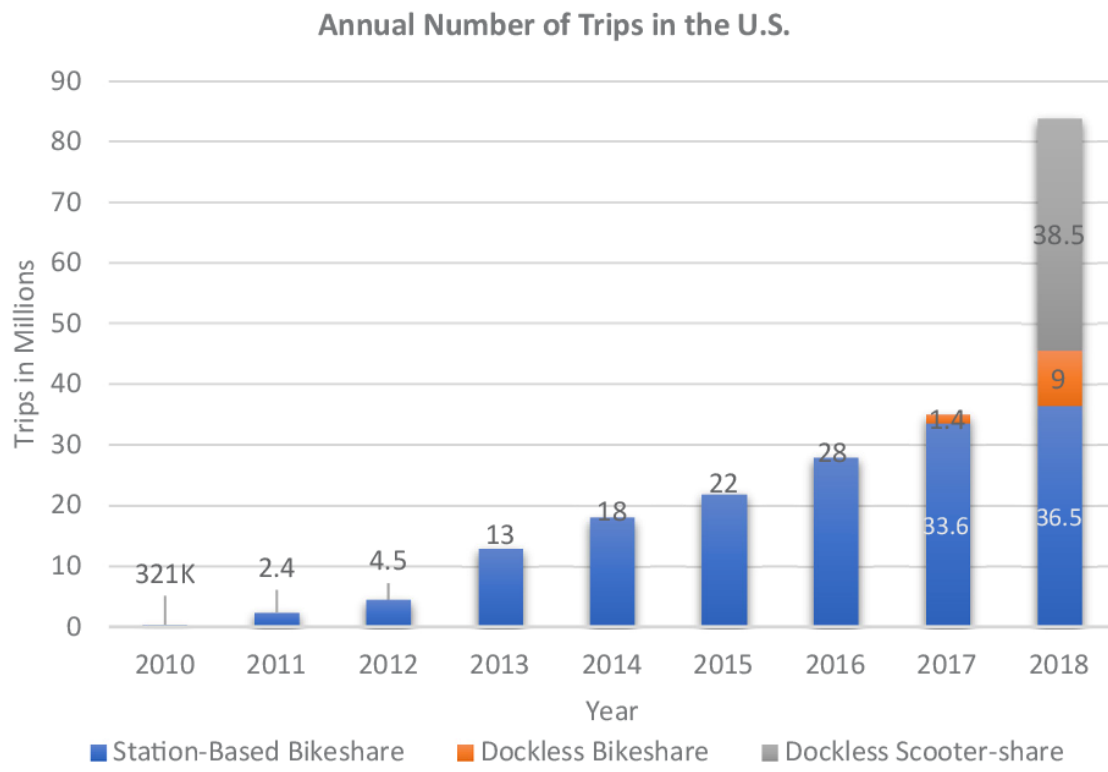


Figure 6 Recent trends in Micromobility in the U.S. Data source: NACTO [17]

The quick growth in dockless micromobility systems has important implications for policy and urban planning decisions relating to transportation and mode choice. However, very few studies have been published on dockless bike- and scooter-share systems [68]. Given how scooters have disrupted shared micromobility, there is interest in investigating how people use these vehicles differently from station-based bikeshare vehicles. This study aims to fill a gap in the literature by empirically examining the determinants of dockless e-scooters using data from bikeshare systems in Washington, D.C.

The contribution of this study is three-fold: (1) to identify the determinants of dockless scooter-share use, (2) to compare the determinants of both systems to understand whether the effects are different, and (3) to analyze if and how the modes interact together. Based on the results of this analysis, we make several policy and planning recommendations to encourage dockless e-scooters as a sustainable, convenient mode of travel and a complement to the existing city-operated SBBS program. The remainder of this paper is as follow: the next section reviews recent advances in both dockless and station-based micromobility; then, we describe the data used in this analysis; followed by the regression methods employed; and a discussion of the results. We outline limitations with our study and finally, provide conclusions, policy implications and future research directions.

Literature Review

Dockless bike-share (DBS) and e-scooter-share (DSS) research was virtually non-existent until 2016. Most of the recent literature on DBS uses small scale survey data. This paper is one of the first to use large scale API data, spanning 6 months of trips. To the best of the authors' knowledge, no study has compared the temporal determinants between DSS and SBBS. Also, because of gaps in the previous literature, it is not clear whether the factors that impact temporal travel behavior vary between these two modes of micromobility.

Dockless Micromobility Research

Recent research on dockless and free-floating bike-sharing typically uses survey data and has focused in Chinese cities. Li et al. (2019) investigated the social factors influencing choice of bicycle among private bike, station-based bike-sharing and dockless bike-sharing in Kunming, China [69]. They found that DBS is most desirable in connecting other travel modes, is an attractive option for young, low-income and student groups, and is desirable for temporary travel demand. Two separate studies analyzed commuting and non-commuting behaviors in Shanghai, China using questionnaires and found that DBS promotes both commuting and non-commuting trips [70, 71].

Luo et al. (2018) analyzed DBS and ride-hailing in New York City and found that multimodal connections between the two modes reduce passenger trip times and decrease road congestion [72]. Ai et al. (2019) sought to measure traveler's tolerance for walking and DBS using GPS data. They found that passengers who transfer from public transit by walking are more sensitive to distance while DBS users are more concerned with time cost of finding an available bike [73]. Mooney et al. (2019) explored equity of spatial access to DBS in Seattle. They found inequity in access DBS along sociodemographic lines, similar to other studies of station-based bikeshare systems. However, they also found that no neighborhood was consistently excluded from access [26]. Our study differs from that of Mooney et al. (2019) in that we analyze equity in outcome (usage) rather than equity in opportunity (supply). However, without equity in opportunity, it is unlikely that we will see equity in outcome.

Shen et al (2018) investigated the impact of dockless bike fleet size on the usage of bikes in Singapore. They performed a regression on the bike fleet size and controlled for transportation infrastructure, the built environment, and weather. While weather was not the main focus of their analysis, they included two variables: precipitation and extreme temperatures. They found that precipitation appears to have a statistically significant negative impact on the number of rides while extreme temperatures (>87.8 ºF) was not significant at the 0.05 level once accounting for spatial dependencies [74].

Luo et al. (2019) conducted a comparative life cycle assessment (LCA) of station-based and dockless bike-sharing systems in the U.S. Their results showed that excluding rebalancing, station-based bikeshare and DBS have a greenhouse gas (GHG) emission factor of 0.148 lb. CO2/mi and 0.113 lb. CO2/mi, respectively. However, including rebalancing causes the GHG emission factors to jump to 0.23 lb. CO2/mi and 0.419 lb. CO2/mi, respectively, making DBS comparable to conventional bus transit. They conclude that a focus on addressing the rebalancing problem is paramount in reducing GHG emissions [19]. While these estimates provide a good starting point for comparing emissions between modes, they are dependent on specific assumptions on a single system and therefore, will have to be adjusted for different regions, behaviors, and modes.

McKenzie (2019) used a similar data processing approach to ours to compare DSS and SBBS systems by scraping API data for Lime Scooters every 5 minutes from June to October 2018. Despite the relatively large scraping interval, the author finds several interesting results. The author identifies spatial and temporal differences and similarities between dockless e-scooters and existing bike-sharing services in Washington, D.C. His findings are that non-member bikeshare ridership is temporally similar but varies substantially in spatial distribution from dockless scooters. Member bikeshare ridership was both temporally and spatially dissimilar from dockless scooters [68]. This study differs from McKenzie’s in that McKenzie addresses distributional differences between the two modes while this one analyzes factors that impact their usage.

Station-based Micromobility Research

Research on station-based bikeshare is more abundant than its dockless counterpart. Many studies have looked at the determinants of bikeshare usage using historical trip data [43, 56, 64, 75-77]. Weather factors are some of the vital determinants of bikeshare usage. Unlike car or transit users, bike users are more significantly affected by weather conditions. El-Assi et al. (2015) found that weather conditions in addition to demographic and built environment characteristics have a large influence on the demand of station based bike-sharing trips in Toronto, Canada [76]. Corcoran et al. (2014) reported that wind and rainfall reduce the number of trips while the temperature effect is limited [63]. Gebhart & Noland (2014) analyzed the impacts of weather on station-based bikeshare activity in Washington, D.C. They used a negative binomial model and controlled for temperature, precipitation, wind, weekend and holidays, peak travel times and darkness, and the number of stations in the system [64]. They found that weather variables had the expected signs and significance on travel behavior. An et al. (2019) found that weather impacts bike-sharing ridership more than topography, infrastructure, land use mix, calendar events, and peak hours [75].

Several studies have analyzed the relationship between bikeshare and other modes [78-82]. This present study places special attention on modal shifts away from gasoline-based auto travel towards more sustainable modes of transportation. Studies related to auto and bikeshare have focused on traffic congestion [83, 84], mode substitution rates [14] and gasoline prices [85]. He et al. (2019) analyzed 5-year temporal bikeshare data at the daily scale for three major U.S. cities and found that the price of gasoline had a positive and significant impact on bikeshare ridership and duration [85].

Special events and disturbances with other modes can also impact bikeshare. Bridge closures, strikes, and transit disruptions have all been shown to impact bikeshare ridership [29, 50, 51, 79]. During the 6-month period covered in this paper, however; there were no major transit closure affecting other modes of transportation. Nevertheless, because of the importance of such disturbances on mobility, we did include two special month-long disturbances that likely impacted mobility in D.C.: The government shutdown in January 2019 and the Cherry Blossom Festival in March 2019. The Washington Metropolitan Area Transit Authority (WMATA)'s metro reported estimated daily losses of around $400,000 due to a decrease in daily rail and bus ridership during the government shutdown and subsequent closure of Smithsonian Museums and National Parks Services [86]. The impact that the shutdown had on micromobility has not been studied. Cherry Blossom Festival, on the other hand, is the annual event in D.C. that attracts an influx of visitors from all over the country and worldwide. We expect to observe a significant increase of micromobility usage during the festival.

The availability of large-scale real time data has made it possible to conduct a temporal regression analysis comparing several important factors that have been empirically proven to be significant on station-based bikeshare, such as wind speed and precipitation. The purpose of this study is to compare these determinants between two modes of micromobility: dockless scooter-share and station-based bikeshare.

Data

The authors collected DSS data by accessing each of the six vendors' (Bird, Lime, Skip, Spin, Jump, and Lyft) API in real time every 30 seconds to 5 minutes depending on the vendor from December 22nd, 2018 to June 21st, 2019. Because vendors can choose how often to update their API, updates vary from being instantaneous (in real time) to refreshing every 5 minutes. Several scraping intervals were tested for real-time API data, and we found that limiting scraping to a minimum of 60 seconds provided an accurate snapshot of trips. Between 0-8% of vehicles had a turnover rate of one minute or less, depending on time of the day. The highest vehicle turnover rate was observed during the Cherry Blossom festival, ergo a time that data were scrapped at 30-second intervals. Attribute information includes the vehicle ID, time stamp, and geographic coordinates for all available vehicles. Once vehicles are reserved, they are absent from the API until they are available again. We process the data by assuming that a bike or scooter that is "unavailable" or absent from the API for longer than 2 minutes designates a trip. We subsequently filter the data by Euclidean Origin-Destination (OD) distance (0.2-10mi), maximum duration (2-90 minutes), and speed (<15 mph based on Euclidean distance) to limit the number of false starts and rebalanced vehicles. Station based bikeshare data are retrieved from Capital Bikeshare (CaBi) Historical data and is similarly processed to include trips longer than 2 minutes, thereby excluding false starts [87].

Out of the six vendors, two of them had data that was complete and continuous for the entire 6-month period and the other four were only complete and/or continuous for a smaller timeframe. Based on the few weeks that we were able to reconstruct complete data and based on our conversation with the District Department of Transportation (DDOT), we estimate that the data from the two vendors comprise around 50% of the total number of dockless trips in Washington, D.C. This is simply an estimate and is likely to vary, with the proportion of trips changing slightly by vendor from month to month. Moreover, this estimate is in line with the NACTO report that showed that in 2018, trips from dockless navigation had surpassed station-based navigation [17]. The purpose of weighing the data is to provide a broader picture of how micromobility is affected by various temporal variables in D.C. overall.

Data were collected from December 22nd, 2018 to June 21st, 2019, covering a 6-month period. Data for the bike sharing systems are aggregated by hour. Each start of trip time is floored to the nearest hour and combined with hourly weather data from the Ronald Reagan Washington National Airport Weather Station [88] and weekly gasoline price data [89].

While vehicle type (bicycle versus scooter) and the micromobility infrastructure (dockless versus station-based) are important factors in travel behavior, the pricing scheme of such systems is one that cannot be ignored [90]. DSS throughout the U.S. generally have the same pricing scheme of $1 to unlock the vehicle and an additional $0.15 per minute of ride. Station-based bikeshare typically have a membership service in addition to their single ride fare. A single ride for

Capital bikeshare costs $2 for the first 30 minutes. Membership costs $85 for an annual pass and $28 for a monthly pass and allows for unlimited 30-minute rides. Dockless vendors in D.C. do not yet offer a membership service, and thus the data were separated in three distinct populations: DSS users, non-member (referred to as "casual") SBBS users, and member SBBS users.

The descriptive statistics from the 6-month period show us that trip duration is similar for both DSS and SBBS. However, casual riders have much longer trips considering that they pay a single fee for a 30-minute time frame. Members have unlimited 30-minute rides included so the trip duration is less important to them. DSS users pay to unlock the ride and then per minute of usage, which explains why the median trip duration is about half that of a casual rider. Given the current pricing scheme, the median DSS trip costs $2.80 (**Table 6**).

Table 6: Summary statistics for the dependent variables.

Vendor		**Median OD Distance Miles**	**Median Duration Minutes**	**Average Speed MPH**	**Average hourly number of trips**	**# Trips (Dec -June)**
Dockless[1]		0.63	11.5	3.63	179.7	727,055
CaBi[2]	**All**	0.95	11.48	5.58	329.8	1,394,289 (40,614 loops)
	Members	0.95	10.43	5.95	281.7	1,209,049 (1.7% are loops)
	Casual	0.96	23.45	3.17	48.1	185,240 (10.6% are loops)
TOTAL (ESTIMATED)					705.4	2*727,055 +1,394,289 =

[1] Based on API data from two vendors (approximately 50% of the trips).

[2] Start or end inside Washington, D.C. boundaries.

						2,848,399[3]

Figure 7 shows the average hourly number of Capital Bikeshare trips (separated by member and non-member) and of DSS trips. The most noticeable aspect of this graph is the clear peak hour activity for station-based trips made by members. Weekday DSS trips tend to be more active in the afternoon than in the morning. Both weekend DSS trips and weekend station-based non-member trips are higher than their weekday counterpart. Within weekday variation is apparent for Monday versus other days, where activity is lower per hour. Within weekends, Saturday activity appears higher than Sunday. Additionally, night activity appears to be higher for Friday and Saturday than for other nights.

[3] This figure is the estimated number of micromobility trips during the 6-month period (processed by the length, duration and speed specified in the data processing section of this paper).

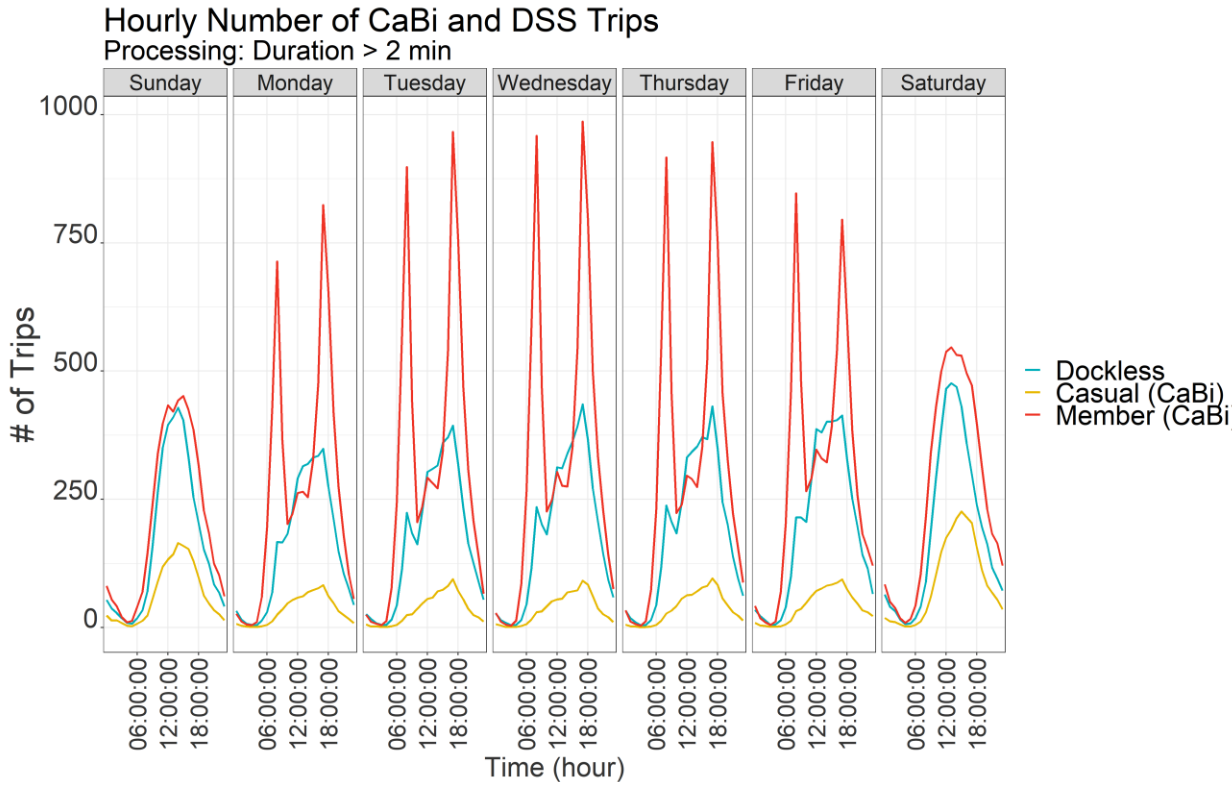


Figure 7: Trip distribution by time of day and day of week based on available unweighted data.

Figure 8 displays the relative change in daily trips from the first week that data were collected. Beyond the expected seasonal patterns, we find that both DSS trips and member SBBS trips increase at a faster rate than casual SBBS trips; with a final relative change of around 300% from the December baseline compared to 100-200% for casual bikeshare riders.

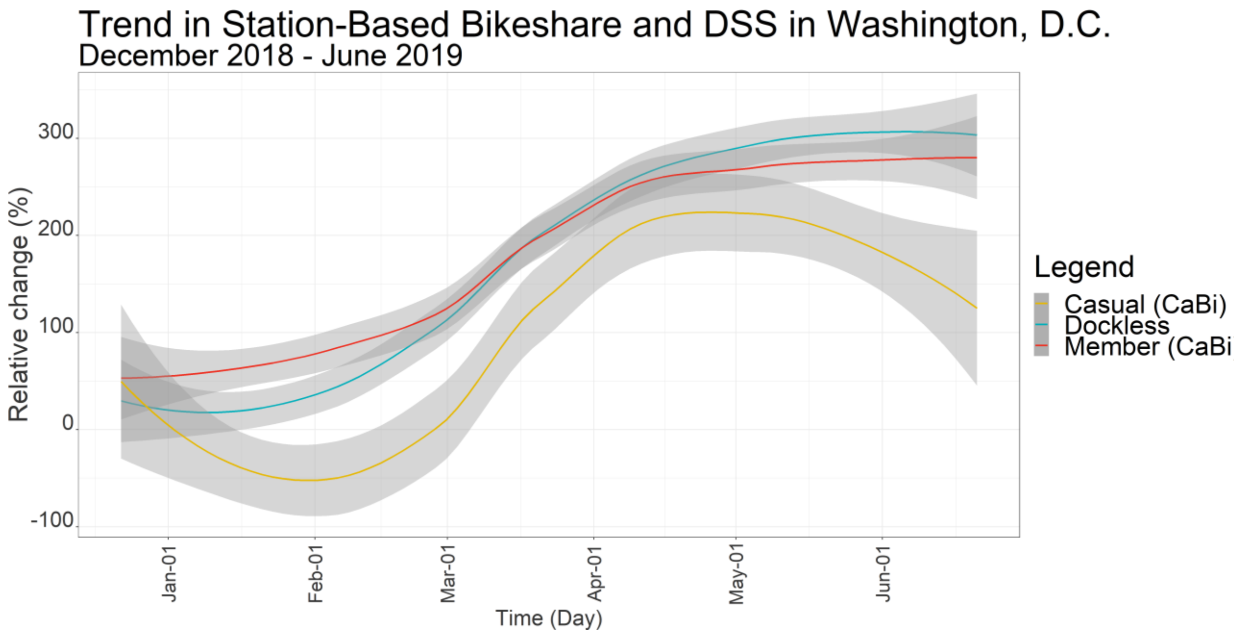


Figure 8: Relative percentage change in daily micro-mobility ridership in D.C. (December 2018-June 2019). The trend line is based on the relative percentage change in daily ridership from the first week average (December 22nd-29th 2018). It is calculated using the Loess regression method (0.95 confidence interval).

Methodology

The purpose of this study is to analyze and compare the temporal determinants between DSS and SBBS. To achieve this objective, we perform models on two dependent variables on three different user groups. The two dependent variables are the hourly number of trips and median hourly trip duration and the three populations are DSS users, non-member SBBS users, and member SBBS users.

Hourly median duration of trip is statistically significantly positively skewed for all three user groups using the D'Agostino test for skewness [91], thus, it is log-transformed in an Ordinary Least Squares (OLS) model that controls for the variables described in **Table 7**. Hourly trip data requires a count time series model [53, 79] and an OLS regression is not appropriate for that variable. A negative-binomial model is deemed more appropriate than a general Poisson model because of statistically significant overdispersion of our data [64, 92]. The negative-binomial model is log-linked, meaning that instead of log-transforming the dependent variable, the linear predictors are exponentiated (allowing for hours with no trips). The model is specified as **Eq. (1):**

$$E_{x_{ik}}^{\lambda_i} = \beta_k x_{ik} = EXP(\boldsymbol{\beta} X_i + \varepsilon_i) \qquad \textbf{\textit{(1)}}$$

where λ is the Poisson parameter (the expected number of events per period) and $\boldsymbol{\beta}$ is the vector of estimable parameters [92].

Our model builds on previous bikeshare and weather models [64] with the following modifications: (1) we consider temperature to be a continuous variable; (2) we use time dummy variables as opposed to darkness and peak hour variables to fully understand the role of midday, evening and night hours on micromobility activity; (3) we use a day of week dummy variable instead of a weekend/weekday dummy because we believe that sufficient variance exists between each day; and (4) we add special events (Cherry blossom festival, Government Shutdown) dummy variables and (5) weekly gas prices.

The dependent variable is the number of trips per hour. We performed the model on four populations: (1) all trips combined and weighed, (2) member SBBS trips (i.e. monthly or annual Capital Bikeshare subscribers), (3) casual (i.e. non-members) SBBS trips and (4) DSS trips. Therefore, we assigned a weight of 2 to the dockless trips in the regression. The total estimated number of trips is therefore equal to the sum of dockless trips (from the two vendors) multiplied by two and of all station-based bikeshare trips: approximately 3 million trips over the 6-month (**Table 6**). This estimation is in line with the only report currently available on micromobility ridership in the U.S., which showed that in 2018, the number of dockless trips was slightly higher than that of station-based trips [17].

Table 7 displays the descriptive statistics of the model determinants. The 6-month period spanned the entire winter and spring seasons in Washington, D.C., allowing for a wide temporal variation in weather variables. Price of gasoline remained within a 56-cent range throughout the duration of the data collection period. Two local disturbances occurred, lasting between three and five weeks in length.

Table 7: Descriptive Statistics of Independent Variables

Continuous	Average	Standard Deviation	Minimum	Maximum
Temperature (^{o}F)	53.12	17.06	10	92
Precipitation (in)	0.0053	0.0293	0	0.62
Humidity (%)	49.66	19.72	1	86
Visibility (mi)	9.40	1.84	0.1	10
Wind Speed (mph)	8.99	5.23	0	34
Gas Price ($/gallon)	2.622	0.202	2.37	2.932
Discrete	Number of independent variables	Reference variable	Time period/Frequency	
Day of week	6	Sunday	Weekly	
Time of day in 3-hour increments	7	3pm-6pm	Daily	
Government Shutdown (weekdays)	1	No shutdown or weekend	Weekdays during December 21st, 2018-January 25th 2019	
Cherry Blossom Festival	1	No Cherry Blossom Festival	March 20th – April 13th 2019	
Holiday	1	Not a major holiday	Six during 6-month period	

Results

Analysis of Hourly Trip Counts

Two dependent variables were analyzed: hourly number of trips and median hourly duration of trips. Five models were fitted on four different groups for the number of trips per hour. The first model encompasses all trips coming from micromobility in D.C. The results of this model can be interpreted as the impacts of different variables on all of micromobility in D.C. The second, third and fourth models are for station-based member users, station-based non-member users (i.e. "casual" users) and DSS users. The fifth model is added to show the interaction of SBBS with DSS. The comparison between user types (i.e. pricing scheme, vehicle type, and station structure type) is made between models 2, 3 and 4. The results are presented in **Table 8**.

Weather: Warmer temperatures and better visibility are associated with higher instances of trips per hour. Conversely, humidity, wind speed and precipitation have a negative impact on number of trips per hour. Casual SBBS users appear to be more sensitive to changing weather conditions as their coefficient is well above that of either DSS or member SBBS users. A likely reason for this difference with scooters is the ease of using free-floating scooters both in terms of physical effort and in convenience of being able to leave the scooter in any permitted area. Members of bikeshare tend to be the least sensitive to changing weather conditions most likely due to the habitual travel behavior of members, the less expensive pricing structure, or not having an alternative mode of transportation. Additionally, we find that DSS users are not statistically sensitive to precipitation at the 0.05 level. We suspect that the ease and convenience of DSS is again a likely reason for this.

Time of day: The times were grouped in 3-hour increments and the reference is afternoon peak (3pm-6pm). For all three dependent variables, afternoon peak is either the highest or second highest time where trip activity occurs. For DSS trips, the midday (12pm-3pm) time is the only time that has a positive coefficient, indicating an association with more trips than 3pm-6pm. For casual and member station-based trips, midday and 6am-9am were respectively not significantly different from the afternoon peak time.

Day of week: Because sufficient variations exist between days, we chose to include all days with Sunday as the reference. DSS and casual SBBS users' peak activity occurred on Saturday, followed by Sunday. For DSS, Friday activity was not statistically significantly different from Sunday. All other days have less trip activity. Members show the opposite effect, with all other days having a significant positive coefficient (except for Monday which is not significant), indicating that trip activity is higher during the week.

Special events or disturbances and holidays: Holidays exert a positive effect on casual SBBS and DSS trips and are associated with fewer member trips. The government shutdown, which lasted from December 21st to January 25th exerted a negative effect on DSS trips but had no significant impact on station-based trips. As expected, the Cherry Blossom Festival, occurring for several weeks in March and April had a significant and positive impact on all types of bikeshare trip activity.

Gasoline prices: Gas prices have a significant and positive effect on micromobility. Increasing gas prices are associated with higher instances of trips (controlling for all other factors). Member trips appear to be the least sensitive to such changes (with a coefficient about 1/3rd that of casual SBBS trips and DSS trips) which is expected considering that members have already committed to using bike as a mode of transportation.

Interaction between dockless and station-based micromobility: Based on the initial relationship in **Figure 3** in the previous section, we attempted to measure the impact of increasing casual user trips and member user trips on DSS trips. We found an interesting association: casual users have a negative and significant coefficient while member users have a positive and significant coefficient. We speculate that the relationship between casual users and DSS users comes from the fact that the targeted population (demand) is similar: both users opt to pay a single trip fare for the vehicle. However, station-based systems have a restricted supply due to bike capacity infrastructure. In times of high demand for bikes, bikes may not be readily available at popular docking stations. As a result, we assert that users resort to using an alternate mode of transportation such as dockless vehicle instead. The tandem increase in DSS activity and member trip activity is likely due to outside forces, such as the increasing popularity in micromobility overall. The regression results confirm the initial visual relationship seen in **Figure 6**.

Table 8: Negative-Binomial Regression Results for micromobility models

Dependent variable: Hourly Number of Trips					
	All Trips (weighed)	**Member (CaBi)**	**Casual (CaBi)**	**Dockless Scooters**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**

Weather Variables					
Temperature (ºF)	0.022***	0.019***	0.038***	0.021***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Visibility (1-10 mi)	0.033***	0.022***	0.053***	0.041***	0.044***
	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
Humidity (%)	-0.007***	-0.008***	-0.012***	-0.006***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wind Speed (mph)	-0.014***	-0.014***	-0.025***	-0.013***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Precipitation (inch) (lagged 1 hour)	-1.138***	-1.461***	-2.278***	-0.733*	-0.313
	(0.348)	(0.360)	(0.414)	(0.378)	(0.334)
Time of day (Reference is 3pm-6pm)					
t0_3	-2.677***	-2.747***	-2.546***	-2.643***	-1.976***
	(0.042)	(0.043)	(0.047)	(0.046)	(0.048)
t3_6	-3.132***	-2.797***	-3.476***	-3.559***	-2.897***
	(0.044)	(0.043)	(0.054)	(0.050)	(0.051)
t6_9	-0.529***	-0.048	-1.397***	-1.059***	-1.374***
	(0.042)	(0.042)	(0.045)	(0.045)	(0.043)
t9_12	-0.351***	-0.350***	-0.333***	-0.354***	-0.115***
	(0.042)	(0.042)	(0.043)	(0.045)	(0.041)
t12_15	-0.129***	-0.401***	-0.020	0.037	0.333***
	(0.040)	(0.041)	(0.041)	(0.043)	(0.039)
t18_21	-0.441***	-0.270***	-0.625***	-0.549***	-0.492***
	(0.040)	(0.040)	(0.041)	(0.043)	(0.039)
t21_24	-1.443***	-1.334***	-1.434***	-1.508***	-0.969***
	(0.041)	(0.041)	(0.043)	(0.044)	(0.044)
Day of week (Reference is Sunday)					
Monday	-0.076*	0.042	-0.755***	-0.140***	-0.278***
	(0.039)	(0.039)	(0.042)	(0.043)	(0.039)
Tuesday	0.032	0.150***	-0.721***	-0.039	-0.228***
	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)
Wednesday	0.039	0.161***	-0.716***	-0.030	-0.238***
	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)
Thursday	0.060	0.169***	-0.626***	0.013	-0.167***
	(0.039)	(0.039)	(0.042)	(0.042)	(0.039)
Friday	0.128***	0.180***	-0.441***	0.121***	-0.020
	(0.039)	(0.038)	(0.041)	(0.042)	(0.038)
Saturday	0.118***	0.136***	0.169***	0.099**	0.102***
	(0.038)	(0.038)	(0.040)	(0.042)	(0.037)
Special Events					
Holidays	-0.059	-0.170***	0.511***	-0.032	0.152**
	(0.061)	(0.065)	(0.071)	(0.067)	(0.060)
Shutdown (Weekdays)	-0.124***	0.048	0.063	-0.351***	-0.334***
	(0.037)	(0.039)	(0.046)	(0.041)	(0.037)
Cherry Blossom Festival	0.185***	0.156***	0.371***	0.195***	0.158***
	(0.029)	(0.031)	(0.033)	(0.032)	(0.028)
Weekly Gas	0.780***	0.347***	1.021***	1.192***	1.111***

Prices ($)	(0.090)	(0.087)	(0.095)	(0.098)	(0.087)
# Casual Trips (CaBi)					-0.002***
					(0.0002)
# Member Trips (CaBi)					0.002***
					(0.0001)
Constant	3.978***	4.373***	0.098	1.534***	1.204***
	(0.203)	(0.199)	(0.219)	(0.222)	(0.197)
Observations	3,801	4,361	4,361	3,808	3,808
Log Likelihood	-25,824	-26,219	-17,159	-20,714	-20,274
McFadden Pseudo R2	0.1477	0.1435	0.2097	0.1635	0.1813
theta	2.629*** (0.059)	2.296*** (0.049)	2.310*** (0.061)	2.300*** (0.056)	2.992*** (0.077)
Akaike Inf. Crit.	51,694.8	52,483.9	34,365.4	41,474.5	40,598.1
Note:	*p<0.1; **p<0.05; ***p<0.01				

Interpretation of coefficients

Elasticities for continuous variables are calculated by **Eq. (2)**:

$$E_{x_{ik}}^{\lambda_i} = \beta_k x_{ik} \tag{2}$$

The pseudoelasticity for indicator variables is calculated by the following **Eq. (3)**:

$$E_{x_{ik}}^{\lambda_i} = \frac{EXP(\beta_k)-1}{EXP(\beta_{k)}} \tag{3}$$

where in both cases, β_k is the estimated parameter for the kth independent variable. The pseudoelasticity gives the incremental change in frequency caused by changes in the indicator variable [92]. The results are displayed in **Table 9**.

A 1% increase in each variable is associated with the corresponding percentage change in the number of trips. For instance, a 1% increase in mean temperatures is associated with a 1.05% increase in member SBBS user trips, a 2.13% increase in casual SBBS user trips and a 1.12% increase in DSS ridership. An important difference between casual SBBS users and DSS users is that, despite their similar temporal behavior, DSS users are much less sensitive to weather factors than casual SBBS users. We contend that the physical ease and the dockless convenience of using scooters is likely responsible for this difference.

Beyond the weather variables, gas price sensitivity shows that a 1% increase in mean gas prices is associated with a 0.92% increase in member bikeshare usage, 2.70% in casual bikeshare usage and 3.13% in DSS usage. Assuming the average of $2.63, an increase of $0.026 would correspond to 1.3 added casual SBBS trips, 2.7 member SBBS trips and 5.8 DSS trips per hour on average. Using the combined all trips weighed regression, this equates to around 14.4 added trips per hour, or 345.6 added trips per day when controlling for all other factors.

The effect of the local disturbances was statistically significant, although of small magnitude. A change in about 1 trip per hour is estimated due to these events. The average number of trips was 0.13% lower during the shutdown. Conversely, the average number of hourly trips was 0.17% higher during the Cherry Blossom festival. While their effects are small in magnitude, such events are important to consider, especially when they last for several weeks.

Finally, the mean elasticity for the station-based bikeshare coefficients in the fifth model were of 0.543 and -0.098 for member and casual user trip frequency, respectively. The mean elasticity of casual bike trips implies that a 1% increase at the mean frequency of casual bike trips (mean = 48 hourly trips) results in a 0.1% reduction in DSS trip frequency or an average reduction in just 0.2 DSS trips per hour. This negative association could indicate a possible substitution between the two modes.

Table 9: Elasticity of coefficients for the negative-binomial model on trip counts

Continuous variables	**All (1)**	**Member (2)**	**Casual (3)**	**Dockless (4)**

(Mean Elasticity) (%)				
Temperature	1.147	1.053	2.131	1.118
Visibility	0.309	0.206	0.503	0.387
Humidity	-0.357	-0.411	-0.617	-0.303
Wind speed	-0.130	-0.128	-0.226	-0.121
Precipitation	-0.006	-0.008	-0.012	-0.004
Gas Prices	2.046	0.917	2.696	3.126
Indicator Variables (Pseudo Elasticity) (%)	**All**	**Member**	**Casual**	**Dockless**
Holidays	-0.061	-0.185	0.400	-0.032
t0_3TRUE	-13.53	-14.60	-11.75	-13.06
t3_6TRUE	-21.93	-15.39	-31.32	-34.14
t6_9TRUE	-0.698	-0.049	-3.04	-1.89
t9_12TRUE	-0.420	-0.419	-0.395	-0.425
t12_15TRUE	-0.138	-0.493	-0.021	0.036
t18_21TRUE	-0.555	-0.310	-0.868	-0.731
t21_24TRUE	-3.24	-2.80	-3.20	-3.52
Shutdown (Weekday)	-0.132	0.047	0.061	-0.421
Cherry Blossom	0.169	0.145	0.310	0.177
Monday	-0.079	0.041	-1.128	-0.151
Tuesday	0.032	0.139	-1.056	-0.040
Wednesday	0.038	0.149	-1.047	-0.031
Thursday	0.059	0.155	-0.871	0.013
Friday	0.120	0.165	-0.554	0.114
Saturday	0.111	0.127	0.155	0.095

Analysis of Median Hourly Trip Duration

A second analysis is conducted to detect whether the temporal determinants outlined in part one of this study have an impact on the median hourly duration of trips for which at least one trip was observed in the hour. This time, three models are fitted on member and non-member SBBS and DSS. Because of the pricing structure of DSS users, who have to pay per minute of ride, we expect this group to be the most sensitive to changing conditions. The regression results are outlined in **Table 10** below.

Temperature appears to have a positive impact on trip duration, humidity and wind speed have a negative influence on trip duration while visibility (i.e. fog) and precipitation have no significant impact on trip duration. Nighttime and early morning is associated with shorter trips, relative to the 3pm-6pm reference. For casual SBBS users and DSS users, the only time associated with longer trips is from 12-3pm. For member SBBS users, 3pm-6pm is the time period associated with the longest trips. Weekdays are associated with shorter trips for all user groups. Saturday trips are longer for member and DSS users but not statistically significantly longer for casual users of bikeshare. Holidays and the Cherry Blossom Festival were both generally associated with longer trips for all user groups; although the coefficient was higher for casual and DSS users. The government shutdown appeared to be associated with longer trips for DSS users; the possible reason for which may be a reduction in work trips and an increase in longer leisure trips.

Finally, increasing gas prices had a statistically significant and positive impact on trip duration for member SBBS (12% increase in trip duration for a $1 change in gas prices) and DSS users (15% increase in trip duration for a $1 change in gas prices). This is an interesting finding for members since the previous analysis showed that members were not as sensitive to changing gas prices as other groups in terms of number of trips taken. This indicates that the additional trips and the current trips could be longer due to changing gas prices. Conversely, casual users have additional trips, but the length is not statistically significantly longer. Given that the average casual user trip is already twice the length of a member user trip, this finding makes sense. DSS users have added trips and longer trips that are of statistical and practical significance due to changes in gas prices. The cost of using DSS becomes more expensive than SBBS after just 7 minutes. Thus, the pricing scheme alone does not explain this difference in gas price sensitivity. A likely reason is the more convenient solution of being dockless, which allows for more efficient first-mile, last-mile travel.

Table 10: OLS Regression results for Hourly Median Duration from SBBS and DSS

	Dependent variable: *Hourly Median Duration (log-transformed)*		
	Member (1)	**Casual (2)**	**Dockless (3)**
Weather Variables			
Temperature (ºF)	0.005***	0.007***	0.008***
	(0.0003)	(0.001)	(0.001)
Visibility (1-10 mi)	-0.002	0.005	0.001
	(0.002)	(0.004)	(0.003)
Humidity (%)	-0.001***	-0.002***	-0.002***
	(0.0002)	(0.0004)	(0.0003)
Wind Speed (mph)	-0.004***	-0.007***	-0.005***
	(0.001)	(0.001)	(0.001)
Precipitation (inch) (lagged 1 hour)	-0.163	-0.269	-0.293*
	(0.111)	(0.225)	(0.157)
Time of day (Reference is 3pm-6pm)			
t0_3	-0.088***	-0.120***	-0.004
	(0.013)	(0.027)	(0.019)
t3_6	-0.029**	-0.317***	-0.255***
	(0.013)	(0.028)	(0.020)
t6_9	-0.058***	-0.311***	-0.329***
	(0.013)	(0.025)	(0.019)
t9_12	-0.033**	-0.019	-0.070***
	(0.013)	(0.025)	(0.019)
t12_15	-0.050***	0.046*	0.036*
	(0.013)	(0.024)	(0.018)
t18_21	-0.075***	-0.133***	-0.178***
	(0.013)	(0.024)	(0.018)
t21_24	-0.113***	-0.137***	-0.107***
	(0.013)	(0.024)	(0.018)
Day of week (Reference is Sunday)			
Monday	-0.026**	-0.069***	-0.204***
	(0.012)	(0.024)	(0.018)
Tuesday	-0.017	-0.080***	-0.211***
	(0.012)	(0.023)	(0.018)
Wednesday	-0.016	-0.128***	-0.201***
	(0.012)	(0.024)	(0.018)
Thursday	-0.050***	-0.098***	-0.207***
	(0.012)	(0.023)	(0.018)
Friday	-0.037***	-0.095***	-0.139***
	(0.012)	(0.023)	(0.018)
Saturday	0.028**	-0.024	0.071***

	(0.012)	(0.023)	(0.017)
Special Events			
Holidays	0.023	0.149***	0.219***
	(0.020)	(0.040)	(0.028)
Shutdown (Weekdays)	0.008	-0.003	0.089***
	(0.012)	(0.025)	(0.017)
Cherry Blossom	0.039***	0.071***	0.062***
	(0.010)	(0.019)	(0.013)
Weekly Gas Prices ($)	0.114***	-0.063	0.140***
	(0.027)	(0.053)	(0.041)
Constant	1.841***	3.065***	5.940***
	(0.062)	(0.122)	(0.093)
Observations	4,351	3,940	3,707
R^2	0.250	0.173	0.390
Adjusted R^2	0.246	0.168	0.387
Residual Std. Error	0.207 (df = 4328)	0.388 (df = 3917)	0.279 (df = 3684)
F Statistic	65.616*** (df = 22; 4328)	37.193*** (df = 22; 3917)	107.268*** (df = 22; 3684)
Note:	*p<0.1; **p<0.05; ***p<0.01		

Discussion

This study sought to compare the determinants of dockless scooter-share and station-based bikeshare using multiple large temporal and spatially detailed datasets on micromobility trips. Because of the differences in pricing schemes (and hence, travel habits) within station-based bikeshare, bikeshare was separated into “members” and “non-members” (i.e. “casual”) users. Several important findings emerged from this analysis.

First, this study confirms that DSS users are more temporally similar to casual SBBS users than to member SBBS users. Intra weekday and weekend variations were evident. Saturday trip counts were statistically higher than Sunday trip counts. Friday appeared to be statistically different from other weekdays. We divided time in 3-hour chunks to analyze any time effects beyond the usual peak/non-peak times. We found that midday (12pm-3pm) was not statistically different from the 3pm-6pm peak time for the casual and DSS users. AM and PM peaks were not statistically different from each other for member dockless usage and both represented the highest trip activity for that user group.

Second, despite their temporal similarity, DSS users were much less sensitive to weather factors than casual users were. The weather elasticities were typically half that of casual users. We attribute this difference to the ease of using scooters, which requires minimal physical effort, and to the convenience of being able to drop the vehicle off very close to a destination. DSS users and member SBBS users actually had very similar weather sensitivities. It is interesting since they are completely different user groups with different spatio-temporal behavior. Unlike the ease of usage of dockless, we attribute the smaller sensitivity of member station-based trips to the pricing structure of the system. For $85 per year (or $28 per month), users receive unlimited 30-minute rides. Moreover, members are typically committed to bikeshare as their mode of transportation and are habitual users who are less likely to be affected by adverse weather conditions.

Third, local disturbances or special events effects were found to be non-negligible in this analysis. The authors recommend that city planners consider these effects in travel demand management. Additionally, this information is of practical importance for planning for the number of vehicles deployed during planned special events or disturbances. Examples would be to rebalance or increase the number of vehicles around the National Mall during the Cherry Blossom festival (or other large events or parades), or to exemplify a more global issue in cities, to increase the number of vehicles around temporarily closed fixed transit stations during a disturbance [79]. For unplanned disturbances that impact the economy, in this case the shutdown of the government, and of major touristic activities such as the Smithsonian Museums and the National Parks Services, in Washington, D.C. for five winter weeks, we calculated that the average overall micromobility ridership was 0.13% less than when the government was open. Although small in magnitude, the reduction in trips appeared to come in majority from DSS activity. Moreover, the impact would have likely been stronger had the shutdown happened during peak season for visitors.

Fourth, we found that all three groups were sensitive to weekly gasoline price changes. Increasing average gas prices by just 1% is associated with an increase of approximately 2% in hourly trips, or 345 daily trips. DSS trips were the most sensitive to increases in gas prices, followed by casual SBBS users. As expected, members were the least sensitive to gas prices. This group of users has already committed to using bikeshare as a major mode of transportation; they are likely not car users or seldom use cars and hence, the price of gas is not as important of an indicator of their behavior as it is for casual or DSS users who pay per ride. Moreover, the price of gas appears to influence trip duration the most for DSS users. This finding has important implications for non-member riders, which now comprise the majority of micromobility trips in the U.S. Cars produce 2-3 times more greenhouse gas (GHG) emissions per passenger kilometer than dockless and station-based micromobility (when accounting for entire lifecycle emissions) [19]. The possible shift from cars to cleaner modes due to gasoline pricing is important to consider for policy makers in reducing emissions and in promoting sustainable shared mobility.

Finally, a fifth model specification was fitted to understand interactions between different micromobility modes. Our findings broadly showed that some interaction exists, namely that casual bikeshare trip activity has a negative relationship with dockless trip activity while that of member bikeshare trip activity with dockless trip activity was positive. With respect to dockless trip activity, this indicates a possible competition with casual station-based activity (i.e. single trip fares) and a complement with member station-based activity (i.e. annual or monthly members). Since dockless vendors do not yet have the option to have a member-based subscription, it is not clear whether dockless micromobility would have an adverse impact on station-based bikeshare as a whole and vice versa. Moreover, the magnitude of the coefficient is relatively small, and further research is needed to confirm this interaction.

Conclusion

DSS users are less sensitive to weather changes than their SBBS user counterparts, while concurrently being more sensitive to changes in gasoline prices. Weather factors have been shown to impact SBBS rates more than other built-environment, calendar events, and time of day factors [75]. The implications of DSS users being less sensitive to weather factors are positive in the respect that it makes DSS more competitive with car and public transportation modes (which are generally less affected by weather factors than bicycles). Indeed, DSS could cut costs in inclement weather-related infrastructure typically associated with biking while also being more environmentally friendly than auto-travel and public transit. Moreover, DSS users appear to be more sensitive to changes in gas prices, which provides a more promising opportunity to analyze modal shifts towards low-carbon shared mobility. The sudden popularity in micromobility could have a significant and positive impact on reducing the effects of climate change [19].

Unlike municipal-owned SBBS systems, DSS programs take advantage of a private-public partnership that can minimize the out-of-pocket cost for the city government to expand its efforts in promoting green transportation. From a policy perspective, complementing SBBS with DSS may be the most cost-effective approach to help meet transportation related climate change targets. Moreover, it is important that city transportation agencies focus on having different pricing structures to accommodate differences in user preference in order to maximize the number of trips. In addition, city planners should coordinate with dockless vendors on how to best use resources during special events. Finally, while DSS is convenient, it also causes controversies that should be addressed through better transportation planning and policymaking, such as clutters of vehicles on sidewalks, risky riding behavior (i.e., riding on auto lanes and riding on pedestrian paths), and vandalism. Supervision from the city together with a close partnership with DSS vendors are key to a successful city-wide micromobility operation. In recent years, travel mode distribution has seen the emergence of new travel modes, most notably shared mobility (i.e., ride share, car share, bike share) but also cleaner modes of car travel such as electric vehicles, and more efficient cars due to automated technology. This shows a potential major shift in the way we travel.

Future research directions include analyzing the spatial differences in dockless and station-based micromobility to complement this temporal analysis. Additionally, we propose analyzing the determinants in other cities with different characteristics (e.g., weather, population density, street network design, built environment, presence of fixed transit) to investigate the spatial determinants of micromobility. Finally, future research could focus on complementing large scale API data analysis with survey data to fully understand attitudinal preferences towards modal shifts to emerging mobility.

Data Limitations

This study has several limitations. First, the authors used only two of the six dockless vendor data which provides somewhat of an incomplete picture of dockless activity. While dockless activity is unlikely to vary greatly between vendors (the temporal trip count correlation between the two usable vendors was 0.77), it would still be useful to have complete dockless data. Second, the usable data comprised only scooter data usage, despite the existence of e-bikes in Washington, D.C. Dockless and station-based e-bikes were not analyzed in this study. Analyzing the same vehicle (with a similar pricing scheme) would isolate the effect of being station-based versus free-floating. Third, the API data were updated by one of the vendors at 5-minute intervals. When using real time API data (updated in real-time) by another vendor, we found that depending on the time of the day, between 0-8% of bikes had a turnover rate of 1 minute or less. This means that potential trip ends and starts were missed, resulting in an underestimation of DSS trips from one of the two vendors, particularly during high demand times. Additionally, even at very small scraping intervals (30 seconds), there is always a possibility of missing a trip end and start of a new trip that occurred within that interval. Lastly, spatial variations were not analyzed in this study. We suspect that the two major variations are with gas prices and with trip distribution due to disturbances.

Chapter 4: Examining Access of Micromobility in 6 U.S. Cities: Spatial Analysis of Dockless Scooter & Bike Trips across the United States

Abstract

This study examines the access of micromobility across six U.S. cities, comprising over 4.5 million people. As micromobility increases in popularity and becomes incorporated in policies and city planning, it is important to understand how disadvantaged and underserved communities access and utilize shared micromobility options. These communities typically have the lowest access to transportation options and thus, opportunities to job, health care, and food. While micromobility has the potential to increase opportunities in low-income areas, it is still unclear how people in low-income areas and high minority areas use these options. Using publicly available API data, this study analyzes how this low-carbon mode is employed in Los Angeles, D.C., Chicago, the NYC area, Detroit, and Louisville. The authors find that the built environment has a strong impact on both the number of trips within a census block group (CBG) and the duration of those trips. Results for CBG level socio-demographic and economic variables were mixed. The percentage of young people tends to be associated with higher trip density particularly in Louisville, D.C., and Los Angeles. Higher minority populations are only associated with fewer trips in Los Angeles, D.C., and Louisville. Higher poverty rate was only associated with fewer trips in Los Angeles and Detroit. In Chicago and the NYC area, both pilots at the time of analysis, none of the socio demographic and economic variables were significant

once spatial dependencies were accounted for. The authors recommend that local agencies and vendors work together to increase access to micromobility in impoverished areas and areas with underserved minorities particularly in well established (non-pilot) micromobility cities.

Introduction and Literature Review

Shared micromobility is the shared and typically short-term use of a bicycle, scooter, or other low-speed mode. It has had an unprecedented increase in popularity since it was introduced in the U.S. over a decade ago. Initially, micromobility consisted of station based bikeshare; in 2018, dockless scooters came to view and quickly became the dominant form of micromobility. Some 136 million shared mobility trips were taken in 2019 in the U.S.; 84 million trips in 2018; and 35 million in 2017 [17, 20]. Sixty three percent of micromobility trips taken in 2019 were taken on dockless scooter-share. Micromobility has the potential to encompass between 8-15% of trips under five miles [16]. The NHTS showed that around 50% of trips were shorter than 3 miles and that among all trips shorter than 1 mile, 60% of them were done using a personal vehicle [93]. There is additional survey-based evidence that micromobility trips are replacing car trips – 45% of people using micromobility reported that their trips would have been done by car or ride sharing [20]. Luo et al. (2019) conducted a comparative life cycle assessment (LCA) of dockless bike-sharing systems in the U.S. and found that riding a dockless bike emits around half the CO2 equivalent emissions of personal vehicles. If rebalancing is done optimally (at zero emissions), dockless bikes have the potential of emitting less than 1/6th that of car emissions [19]. It is evident that micromobility is a low-carbon form of transportation. Other documented impacts of micromobility include economic development and health benefits [16].

Ideally, micromobility could improve access to opportunities to those in disadvantaged communities – communities with poor access to transit and personal vehicles. This study examines access of micromobility across 6 U.S. cities in September 2019. We use built environment data, socio-economic data, and control for points of interests in order to analyze the determinants of dockless scooter and bicycle use. The cities in this study are the New York City area, Los Angeles, Chicago, Washington, D.C., Detroit, and Louisville. The cities vary widely in terms of their population, density, socio-economic attributes, and built-environment, and present an opportunity to analyze micromobility usage at a multi-city scale. We begin with a literature review of micromobility as a whole, then focus on recent findings in dockless micromobility and its determinants of usage. Next, we describe the data processing methods and report descriptive statistics. We then report the results of the hot spot analysis and the spatial regression. Finally, we discuss the findings and provide recommendations for policy makers.

Micromobility

Research on station-based bikeshare spans over a decade, while research on free-floating or dockless micromobility is more recent. Unlike station-based micromobility, dockless micromobility is not constrained to a vendor-selected station location. The two systems also differ in pricing structures, with dockless being on average slightly more expensive per trip [20]. Micromobility can be electric or pedal-based. By design, e-bikes and e-scooters allow for higher speeds at a higher level of comfort than conventional bicycles [94]. Several works have sought to compare the differences between station-based and dockless modes [23, 68, 95, 96]. McKenzie (2019) found that station-based bikeshare was more likely to be used for commuting purposes [68]. Younes et al. (2020) found that weather was less of a disutility for dockless scooter-share users [95]. Reck et al. (2020) found that increasing fleet provided only marginal utility past a certain point [23]. Micromobility requires rebalancing, the impacts of which have been understudied due to data availability. Generally local transportation departments provide some guideline on how to rebalance the vehicles [97]. Nonetheless, the trip patterns still suffer inevitable bias from rebalancing. Moreover, pricing is an important component for transportation access. Requirements for discounted programs vary from city to city. According to NACTO's regulation guidelines, Chicago and Washington, D.C. are among those who require operators to provide programs for non-smartphone users. Washington, D.C. goes one step further by requiring that operators also have a low-income customer plan in place [97]. Nonetheless, people typically need a smartphone in order to unlock a vehicle, which may limit usage in low-income communities – around 15% of Americans do not own a smartphone [98].

Determinants of Dockless and Station-Based Micromobility

The impact of the built environment on bikeshare activity has been analyzed widely in the literature [45, 80, 84, 99-102]. Similarly, station-based bikeshare and public transportation has been studied broadly over the last few years [29, 70, 78, 82, 103-107]. Dill & McNeil (2020) reviewed the literature on shared mobility and equity. They found that the majority of bikeshare studies show that lower income populations have lower accessibility and usage [108]. Dockless bikeshare and scooter-share, on the other hand, have not been analyzed as extensively [74, 94, 108-110] and has in majority focused on a single city [23, 26, 68, 72, 74, 95, 111, 112]. Shen et al. (2018) found that access to public transit, bike infrastructure and several other built environment factors are critical to increasing dockless ridership [74]. Ma et al. (2020) found that the density of entertainment points of interest is positively correlated with the usage of dockless bikesharing but negatively correlated with docked bike-sharing usage [96].

Income and other socio-demographic variables have been analyzed in more recent studies [26, 102, 111, 113]. An opt-in survey found that scooter usage for Baltimore's Black/African American population is on par with the population ratio while Washington D.C.'s Black/African American population scooter usage is less common than for White residents [20]. A separate survey in Portland found that 71% of Portland's Black/African American population and 74% of the low income population viewed e-scooters positively [114]. In D.C., a 2018 survey showed that adoption rates were lower for Black/African Americans than for Whites, but that the gap was smaller for dockless (16% adoption rate for Blacks/African Americans vs 25% for Whites) than for docked micromobility (6% for Blacks/African Americans vs 20% for Whites) [115]. Mooney et al. (2019) found that neighborhoods in Seattle, WA with more educated residents had modestly more bikes [26]. Nasri et al. (2020) found that neighborhood income was a significant factor in station-based bikeshare ridership for Boston, Chicago, Washington, D.C., and San Francisco, but not for Minneapolis and Philadelphia. The minority percentage in a census block group

(CBG) was negatively associated with bikeshare ridership in all cities except for Philadelphia [102]. Caspi & Noland (2019) found that low-income neighborhoods in Philadelphia did not generate as many station-based bikeshare trips as other neighborhoods [113]. Caspi et al. (2020) found that less affluent neighborhoods with high usage rates had high student populations, suggesting that students use dockless micromobility as a mode of travel [111]. Jiao & Bai (2020) found that e-scooter trips in Austin, TX were correlated with lower income populations and higher educated populations [116].

The authors know of only one published study that has compared usage in two cities for shared dockless scooters specifically [93]. Bai & Jiao (2020) used hotspot spatial analysis and negative binomial regression models and found that the densest scooter usage happened in downtown areas and university campuses for Minneapolis and Austin. Commercial areas and parks were associated with more trips only in Austin. This study raised the importance of local uniqueness in terms of usage for dockless micromobility [93]. A multi-city analysis is beneficial in that it will provide policy and planning insights at a national scale.

Data and Descriptive Statistics

Description of Study Areas

Data for 7 cities have been collected by the authors by accessing publicly available API for the month of September 2019 (**Figure 9**) [117]. The data were retrieved every 60 seconds for one to two vendors in seven cities and processed similarly to (Younes et al. 2020) [95]. The cities include the New York City area (Staten Island, Rockaway Park, Yonkers and White Plains); Chicago, IL; Los Angeles and Santa

Monica, CA; Washington, D.C. and Northern Virginia; Detroit, MI; and Louisville, KY. Data were also collected for Miami, FL; however, the data quality was poor, and the city was excluded from the main analysis (See Supplementary Material for Data Quality check). Public sources of scooter-share data are not widely available, although several cities have started to publish such data [118, 119]. Among the 6 cities in this study, Washington, D.C. and Los Angeles have the highest ridership in the U.S. [20]. During the time that the data were collected, New York City and Chicago were more popular for their station-based bikeshare system and dockless micromobility was unavailable in their central business district [20].

Aside from the NYC area, data are available only for selected vendors; thus, while cities may have up to 10 vendors in the area, only those who provide quality data are selected (**Table 11**). This means that the number of trips per CBG is not absolute; it must be interpreted as relative to other CBGs.

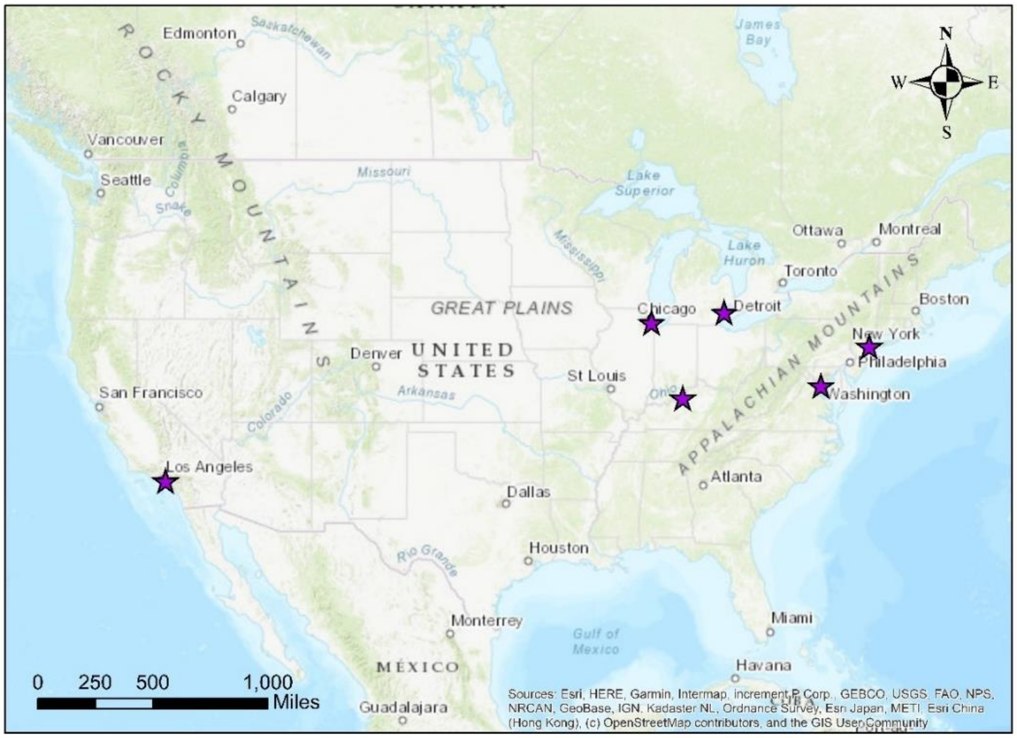


Figure 9: Map of Study Area

Table 11: Scooter Data Description

Company	City	Time Period (Year: 2019)	Number of trips (>2 minutes, <90 minutes)	Vehicle Type	Total number of vendors in the area in September 2019
Lime & Jump	Chicago, IL (not including downtown)	8/25-9/25	23,264	Scooters	10
Lime & Jump	Los Angeles & Santa Monica, CA	8/25-9/25	99,658	Scooters and Bikes	8
Lime	Detroit, MI	8/25-9/25	35,259	Scooters	4
Lime	D.C. & Arlington, VA	8/25-9/25 (9/06 omitted due to glitch in data acquisition)	135,194	Scooters	8
Lime	NYC area – Rockaway park, White Plains, Staten	8/25-9/25	17,121	Bikes	1

	island, Yonkers				
Lime	Louisville, KY	8/25-9/25	19,526	Scooters	3
Bolt	Miami, FL	2/3-2/13/2020	2,853	Scooters	4 [120]

Ground Truth Analysis

Aside from the NYC area, the cities in this analysis all allow more than one vendor. Therefore, there is a question of whether the data from one vendor can represent data from multiple vendors spatially. Few cities provide open source processed micromobility trip data; however, API data is more widely available. Louisville, KY is one such city that provides open source micromobility data and has API data available for one of its vendors, and thus an opportunity for a ground truth analysis to discern whether API data can be spatially representative of ground truth data. For the time period of 8/25/2019-9/25/2019, some 64,157 trips were taken with all four of its vendors (micromobility data) while 19,526 trips took place from a vendor (API data). The mean length for the trips was 11.1 minutes for the ground truth data and 12.1 minutes for the API data. This one-minute discrepancy is likely due to the 1-minute scraping interval data: (a) a trip end will be rounded up to the nearest minute due to the scraping interval and (b) some trip ends and starts within 60 seconds may be missed if the overturn is high. Overall, the duration difference is not meaningfully large (**Figure 10**). The datasets were spatially joined to census block group data and a paired correlation analysis was performed for CBGs that had at least one trip end (from either data source). The correlation analysis was between the following variables: trip ends from all vendors per census block group and trip ends from one vendor per census block group. The Pearson coefficient is 0.9747, indicating that data from API, once processed by the authors can well represent ground truth data spatially. Since the level of analysis is at the CBG level for our spatial models, we are confident that API data can represent "true" micromobility.

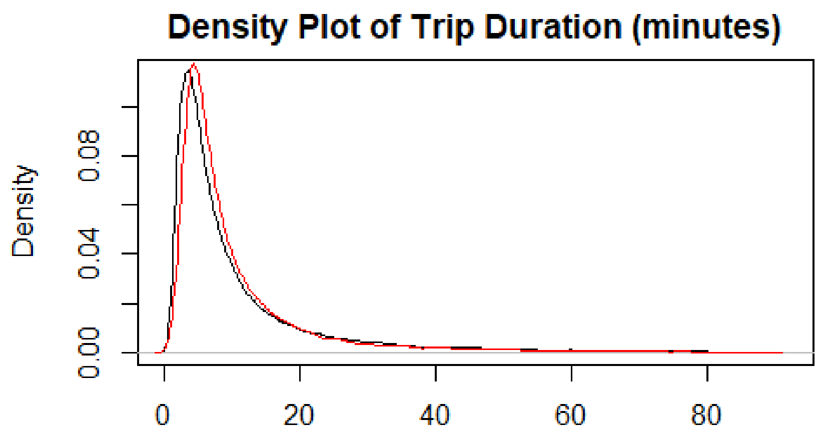


Figure 10: Density Plot of the Trip Duration for API data (red) and Open-Source data (black)

Descriptive Statistics

As displayed in **Table 13**, the cities vary widely in terms of their built-environment and socio-economic demographics. The statistics for the cities are compiled for CBGs that had at least one trip in September 2019. Trips in Los Angeles cover the widest area and the highest population with over 2 million people; trips in Detroit cover the smallest area and the lowest population with around 140,000. Population and job density are highest in D.C. and lowest in Louisville. Consequentially, Louisville has the highest proportion of people who drive alone to work; nearly 75% - while D.C. has the lowest percentage of people who drive alone to work at 40%. The cities span a wide range socio-demographic makeup with the least diverse occurring in Louisville. The average income ranges between $30,000 in

Detroit and over $100,000 in D.C.; similarly, 34% of Detroit and 12.6% in D.C. live under the poverty line.

For the trip density, a model is performed for each of the cities. The dependent variable is the natural log of the number of trips per square mile in a CBG. The natural log is taken because both the distribution of the dependent variable and the residuals of the untransformed model are heavily skewed to the right for all 6 cities. Additionally, it allows for an interpretation of change as a percentage. Trip arrivals will provide a more accurate snapshot of trip activity than trip starts since starts are prone to being rebalanced. For trip duration, models are at the trip level and require more robust analysis. Trip duration is analyzed both temporally and spatially at the daily, weekly and monthly scale.

The independent variables at that same scale comes from the following public access sources: the Transit Oriented Database (TOD) for presence of fixed transit in a census block group [121]; the EPA's Smart location database [122] (2010) for built environment and accessibility measures; the American Community Survey [123] (2018) for socio-economic and transportation characteristics; and the PUMS [124] (2018) for socio-demographic characteristics. Moreover, we use point of interest data (POI) data to identify the presence of universities and parks [125] (**Table 12**). Not all variables are used in the final model due to high variance inflation factor and high correlation between variables. The percentage of people with bachelor's degrees or higher led to too high of a VIF in the models. The presence of a university in a CBG was not as informative as the percentage of 18–21-year-olds in a CBG. In Louisville and Detroit, we could not use the percentage of people with no car as it led to too high correlation with other independent variables. Moreover, robust fixed transit infrastructure is not available in these two cities, so the "Number of Transit Stations" is omitted.

Table 12: Summary of data sources for independent variables

Variable	Scale	Source
Median Household Income	Census Block Group	ACS 2018 5-year survey [123] [124]
Percent of Population below Poverty Line	Census Block Group	ACS 2018 5-year survey
% of Minorities (Hispanic/Latino and/or Black/African American)	Census Block Group	ACS 2018 5-year survey
Education level (% with Bachelor's degree or higher)	Census Block Group	ACS 2018 5-year survey
Age measure (% of College Aged students, % of 22-29, % 30-39)	Census Block Group	ACS 2018 5-year survey
Vehicle ownership (% with no car, % with 2+ cars, % who drive to work alone)	Census Block Group	ACS 2018 5-year survey
Road density	Census Block Group	Smart Location Database (2010) [122]
Population density	Census Block Group	Smart Location Database (2010)
Employment density	Census Block Group	Smart Location Database (2010)
Household and Employment Entropy	Census Block Group	Smart Location Database (2010)
Accessibility and frequency of bus transit	Census Block Group	Smart Location Database (2010)
Accessibility by car	Census Block Group	Smart Location Database (2010)
Presence of fixed transit	Census Block Group	TOD (2020) [121]
Presence of Universities	Census Block Group	USGS (2010) [125]
Local, State, and National Parks (% of area of CBG)	Census Block Group	(2020) [126] [127]

To understand the cities at hand, we conducted a Wilcoxon Rank Sum test to see if any of the cities had similar distributions in terms of their log-transformed trip density in each census block group (**Table 14**). The test essentially tells us if two samples come from the same population. We found that DC and Chicago were not statistically different from each other in terms of trip density distribution. LA and the NYC area; and Louisville and Detroit also had non-significantly different trip distributions. **Table 13** displays the descriptive statistics for some of the variables in the model for the 6 selected cities. It is worth noting that the cities vary widely in terms of their built environment and socio-demographic make-up.

Table 13: Descriptive Statistics for Model Variables

	LA	Chicago	D.C. and Northern VA	NYC Area[4]	Detroit	Louisville
Average Number of Monthly Trips per CBG (September 2019)[5]	70 (2 vendors)	60 (2 vendors)	282 (1 vendor)	51 (1 vendor)	225 (1 vendor)	117 (1 vendor)
Average Population per CBG	1548	1335	1464	1532	858	1119
Total Population (in CBGs with at least two trips in one month)	2,213,358	764,842	857,184	493,380	139,236	184,125
Total Area Covered in sq mi (for census block groups with at least one trip)	222.87	53.28	62.78	71.06	37.14	64.71
Average Job Density (Jobs/Acre)	11.6	8.1	18.8	7.9	7.7	5.2
Average Population Density (People/Acre)	30.7	31.6	32.4	31.9	9.8	9.4
% of No Car Owners	14.5	23.2	27.5	26.6	29.1	18.1
% of people who drive alone to work	65.2	51.0	40.0	50.2	63.8	72.7
% of Hispanic	40.0	42.4	13.4	29.9	8.7	3.2
% of Black/African American	7.6	27.5	33.2	22.6	62.0	28.7
% of people with bachelor’s degree and above	40.4	31.8	62.5	35.7	24.6	33.2
Average Median Income	68,238	55,077	106,807	76,076	29,532	44,425

[4] Includes only Staten Island, Yonkers, White Plains, and Rockaway Park (Queens)

[5] The average number of trips is unadjusted for multiple vendors. Only vendors for which quality data were available were used in this model and analysis.

% Under Poverty Line	19.1	20.1	12.6	16.3	34.3	22.8

Table 14: Wilcoxon Rank Sum Test for Dependent Variable

P value for Wilcox test for dependent variable (ln(y))	DC	LA	CHI	DET	LOU	NYC
DC	1					
LA	< 0.001	1				
CHI	**0.20**	< 0.001	1			
DET	< 0.001	< 0.001	< 0.001	1		
LOU	< 0.001	< 0.001	< 0.001	**0.944**	1	
NYC Area	< 0.001	**0.57**	< 0.001	< 0.001	< 0.001	1

Methodology and Results

The authors first use Hot Spot analysis to understand how micromobility trips cluster spatially for all different cities. We use fixed distance band and Euclidean distance in the ArcGIS platform. We then perform a spatial regression analysis for each of the six cities to understand if and how the built environment, socio economic variables, and socio demographic variables impact CBG trip density. Finally, we finish with an analysis on how the aforementioned variables impact the duration of trips.

Hot Spot Analysis

Dockless bikeshare and scooter share is deployed differently depending on the city. Some cities place emphasis on docked bikeshare (i.e. Chicago and NYC) while others are mostly dominated by dockless systems (Los Angeles and D.C.) [20]. Vendors usually work with local transportation departments to deploy vehicles and are often capped with the number of vehicles that can be made available, the times that vehicles can be used and the zones that they can be taken to. These constraints must be taken into account when analyzing trip density and duration, as it is not solely controlled by the consumer. Additionally, only one or two vendors are analyzed for each city, when more are available. Louisville provided ground truth data and we found that one vendor could spatially represent usage from all vendors (Pearson Correlation: 0.9747).

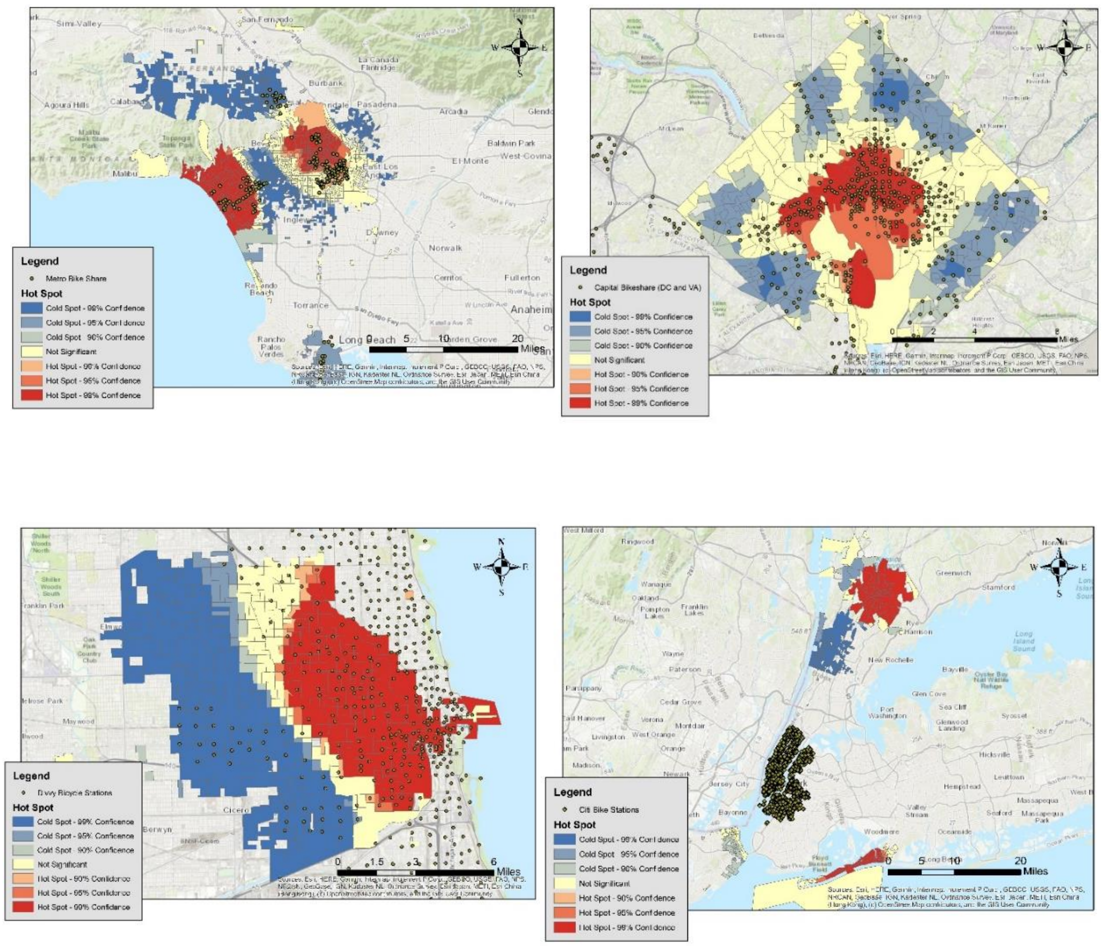
We use ArcGIS to conduct a Hot Spot analysis (Getis-Ord Gi*) using fixed distance band and Euclidean distance method (**Figure 11**). The Getis-Ord Gi* statistic tells us where features with either high or low values cluster spatially [128]. A statistically significant hotspot will have high values surrounded by other high values. The spatial unit is the CBG, and the variable is trip density. We only consider the destination of trips in this study to avoid artificially including origins that are vendor-selected (rebalanced bikes).

We find that hot spots are generally concentrated closest to the city center. Los Angeles has two hotspots: one in Santa Monica and one in Downtown Los Angeles. The city had 8 vendors at the time of data acquisition, with two of them publicly reporting reliable API [129]. It also appears to be well served by station based bikeshare, although many parts of Santa Monica benefit from the dockless system where docked bikes are not available. The D.C. and Northern Virginia area had the same number of vendors as Los Angeles in September 2019 [130]. The D.C. area has dockless scooters in D.C., MD and VA but only provide public API for D.C. and VA. Hence, the analysis does not include trips taking place within Maryland [117]. Based on this subset analysis, hot spots have been identified in Downtown D.C. (central business district) and in northern Arlington, another high employment center. The local transportation department in D.C. requires that 20 vehicles per vendors be available in all wards each morning [131], which includes traditionally underserved Southeast D.C. – a cold-spot in this analysis.

The NYC area and Chicago do not make dockless usage available in their city center. The NYC area is a special case because it is essentially four areas where only Rockaway Park and White Plains are hotspots. Rockaway park is known to be a transit desert with few low-carbon transit options [132]. The towns are from different counties (aside from White Plains and Yonkers) and the vendor is likely subject to different rules about bike deployment. To the best of the author's knowledge, only one vendor was available in the four towns in September 2019 and hence, this is likely to be a complete picture of dockless activity [133, 134]. Moreover, CitiBike does not serve these areas. Chicago, at the time of analysis, was operating a pilot program with 10 companies and did not allow dockless vendors to operate in the downtown area – where the focus was instead placed on docked bikes [135]. The city identified two priority zones located in the western part of Chicago, where at least 25% of scooters must be available each morning [135]. Despite these priority zones, the hot spot analysis (which is based on trip ends) designates the entire area as a cold spot. A few months later, Chicago began a separate pilot program within its downtown borders to allow up to 10,000 scooters [136].

Detroit had three major dockless vendors in September 2019, where each were allowed to have up to 300 vehicles downtown and midtown and at least 100 vehicles in other areas (for up to 400 vehicles total) [137, 138]. The city is additionally served by station-based bikeshare, although it appears to be prominent only in its downtown and midtown area. Detroit hot spots are concentrated along the Detroit River.

Louisville had four vendors available at the time or data acquisition. The cap per vendor was 250 vehicles [139]. The city is not well served by station-based bikeshare; dockless scooter-share appears to cover a much wider area in comparison. Most of the city either has hot spots for scooter trips or is insignificant. The central business district is a hot spot, similarly to other cities.



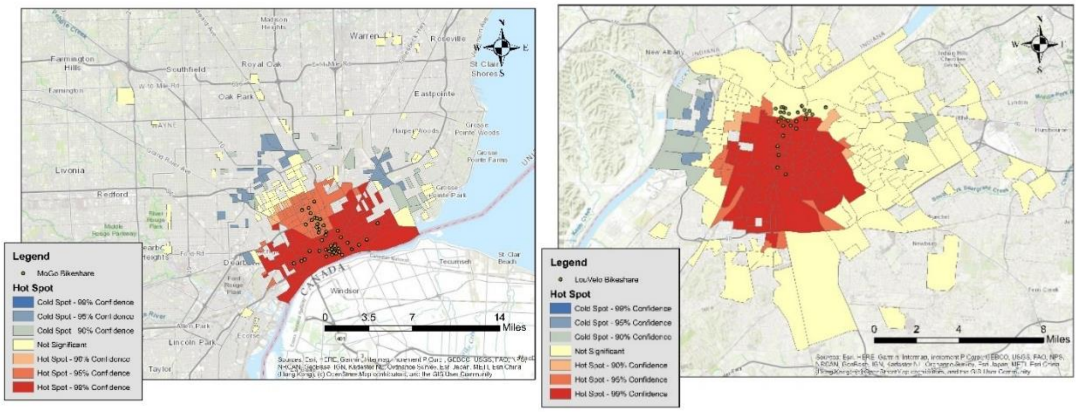


Figure 11: Hot Spot analysis for Los Angeles, D.C., Chicago, NYC Area, Detroit, and Louisville (left to right, top down)

Spatial Regression Analysis

A log-linear OLS regression is performed for the six cities. However, both the dependent variable and the residuals of the models for all of the cities are spatially autocorrelated using Queen's contiguity for spatial weights. As a result, the OLS regression is not the best model for this analysis. We use the AIC and the Lagrange multiplier test and find that the best model for Chicago is the Spatial Lag model and for all other cities, the Spatial Error model is more appropriate. This full analysis is in the supplementary material.

Due to significant spatial auto correlation in the dependent variable and in the residuals of the OLS regression, a spatial model is warranted (see Supplementary Material). The dependent variable is statistically significantly (p-value < 0.001) spatially autocorrelated for all six cities (Moran's I = 0.80, 0.84, 0.70, 0.67, 0.74, and 0.69 for LA, D.C., Chicago, NYC, Detroit, and Louisville, respectively), which indicates that trip density in nearby CBGs influences trip density in a CBG. The residuals of the OLS model are spatially autocorrelated as well using Queen's contiguity (0.63, 0.37, 0.37, 0.27, 0.41, 0.36 for LA, D.C., Chicago, NYC, Detroit, and Louisville, respectively all with a p-value < 0.005). We analyzed the AIC of each model based on either Queen's or Rook's contiguity for each city [140]. The spatial error model considerably improved the AIC from the baseline model (See supplementary material for AIC and Lagrange Test reports). Chicago is the only city where the lag model performs better than the error model. The variable "% of population with no car" is omitted in the Detroit and Louisville models because of high VIF during the OLS regression.

The spatial lag model is specified as **Eq. (3)**:

$$y = \rho \boldsymbol{W}\boldsymbol{y} + X\beta + \varepsilon$$

In the spatial lag model, the outcome is assumed to be dependent on the observable outcomes of neighboring regions. The error term and regressors are thus correlated and OLS is no longer considered an unbiased and consistent model [141] . Rho is the spatial multiplied of y. It shows how y and spatially lagged y are spatially dependent. Interpretively, if spatially lagged y increases by 1 unit, then y increases by rho units. Rho = 0 indicates no spatial dependence and that OLS is appropriate.

The spatial error model is specified as **Eq. (4)**:

$$y = X\beta + \varepsilon$$

$$\varepsilon = \lambda \boldsymbol{W}\varepsilon + \mathrm{u}$$

In the spatial error model, the assumption is that the region's behavior or outcome is correlated with the unobservable characteristics of its neighbors. The outcome is thus dependent on error ε. The term u is not correlated across space and assumed to be normally distributed. Where the spatial lag model primarily controls for spatial autocorrelation in the dependent variable, the error model controls for spatial autocorrelation in both the dependent and independent variables [141]. Lambda is the error simultaneous autoregressive spatial multiplier. It measures whether there is spatial correlation between the errors for connected observations *i* and *j*. The results are in **Table 15** below. Maps of residuals for OLS and Error models (lag model for Chicago) are available in supplementary material.

Table 15: Spatial Model Results

	Dependent variable:					
	Ln (trip density per CBG)					
	LA(1)-(error queen)	**DC(2) -(error queen**	**CHI(3)-(lag Queen)**	**NYC(4)-(error Queen)**	**DET(5)-(error Queen)**	**LOU(6)-(error Queen)**
Gross Population density (people/acre)	0.011^{***}	0.005^{***}	0.010^{***}	0.010^{***}	0.029^{***}	0.057^{**}
	(0.001)	(0.002)	(0.003)	(0.003)	(0.011)	(0.028)
Gross employment density (jobs/acre)	0.002^{***}	0.003^{***}	-0.009^{***}	0.011^{***}	0.002	-0.007
	(0.0007)	(0.001)	(0.001)	(0.003)	(0.003)	(0.006)
Employment and Household Entropy	0.763^{***}	0.560^{***}	0.531^{***}	0.388	0.693^{***}	0.223
	(0.101)	(0.136)	(0.155)	(0.237)	(0.222)	(0.304)
Aggregate frequency of transit service within 0.25 mi of CBG per hour	-0.00001	0.0006^{**}	0.0015^{**}	0.007^{***}	0.0036^{***}	0.005^{***}
	(0.0001)	(0.0003)	(0.0007)	(0.002)	(0.001)	(0.001)
Aggregate frequency of transit service per square mile	-0.000001	0.00002	-0.00002	-0.0001	0.0001	0.0007^{***}
	(0.000004)	(0.00002)	(0.00004)	(0.0001)	(0.0001)	(0.0002)
Total road network density	0.020^{***}	0.009^{**}	0.0013	0.013^{*}	0.017^{*}	0.030^{**}
	(0.003)	(0.004)	(0.006)	(0.007)	(0.010)	(0.015)
Working age population within 45 minutes auto travel time (in 1000s)	0.002^{***}	0.016^{***}	0.002^{**}	-0.002^{***}	0.00002	0.041^{***}
	(0.0004)	(0.002)	(0.0007)	(0.0006)	(0.002)	(0.007)
% of CBG that is local, state, or national Park	-0.008^{***}	-0.003	0.003	-0.009^{**}	-0.003	-0.017^{**}
	(0.003)	(0.002)	(0.004)	(0.004)	(0.007)	(0.009)
% of population that drives to work alone	0.0008	-0.0002	0.001	0.001	-0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)

% of the population with no car	0.004	-0.0001	0.002	0.002	Omitted	Omitted
	(0.002)	(0.003)	(0.003)	(0.004)		
% of population with 2 or more cars	-0.011***	-0.009***	-0.001	-0.010**	-0.011***	0.004
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)
Number of fixed transit stations in CBG	0.122	0.219**	0.406***	0.073	N/A	N/A
	(0.078)	(0.083)	(0.094)	(0.129)		
Area of CBG in sq mi	-0.418***	-1.017***	-3.542***	-2.033***	-1.584***	-0.349*
	(0.035)	(0.124)	(0.607)	(0.247)	(0.297)	(0.196)
% Age 18-21	0.011***	0.012***	0.011	-0.004	0.009	0.034***
	(0.003)	(0.004)	(0.007)	(0.013)	(0.008)	(0.008)
% Age22-29	0.014***	0.013***	0.006	0.001	-0.004	-0.007
	(0.002)	(0.003)	(0.004)	(0.007)	(0.006)	(0.009)
% Age 30-39	0.013***	0.025***	0.016***	0.002	-0.002	0.004
	(0.003)	(0.005)	(0.005)	(0.007)	(0.007)	(0.011)
% Under the poverty line	-0.005**	0.0024	-0.004	-0.006	-0.012***	-0.001
	(0.002)	(0.004)	(0.003)	(0.005)	(0.003)	(0.006)
% of Black/African American or Hispanic/Latino	-0.005***	-0.004**	0.0001	-0.003	-0.001	-0.013***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)
Median Household Income (in 1000s)	0.0007	0.0005	0.0004	-0.002	0.005	-0.002
	(0.0007)	(0.0001)	(0.001)	(0.001)	(0.003)	(0.003)
Constant	-13.497***	-16.287***	-4.8457***	-8.332***	-12.728***	-19.517***
	(0.446)	(0.859)	(0.715)	(0.514)	(0.801)	(1.243)
Observations (N)	1,423	583	573	281	248	211
Rho (autoregressive lag coefficient)			0.69203			
Lambda (autoregressive error coefficient)	0.91521	0.82026		0.6396	0.86004	0.69663
LR Test Value	1474.9***	235.97***	273.95***	61.54 ***	174.63 ***	69.726***
Asymptomatic Std. Error	0.012153	0.027272	0.033951	0.04995	0.023344	0.052394
Wald Statistic	5670.8***	904.61***	415.48***	164***	1357.3***	176.78***
Log likelihood	-1613.634	-604.8844	-607.7432	-308.015	-308.4564	-275.4058
AIC	3271.3 (4744.1 for lm)	1253.8 (1487.7 for lm)	1259.5 (1531.4 for lm)	660.03 (719.57 for lm)	656.91 (829.55 for lm)	590.81 (658.54 for lm)
Note:	Number in parenthesis represents the standard error *p<0.1; **p<0.05; ***p<0.01					

Vendors are subject to restrictions and constraints from local departments of transportation (in terms of where the vehicles can be, at what time, and how many can be deployed). Hence, the models cannot paint a complete picture of how users *would* use vehicles as they are not available everywhere at all times. We interpret the effect size for continuous variables, where β is the coefficient, with the following formula **Eq. (5)** [65, 66]:

$$\%\Delta y = 100 * (e^{\beta} - 1)$$

For a one-unit change in independent variable *x*, we expect the relative change in *y* to be the exponent of the coefficient of *x* minus one multiplied by one hundred percent.

Built Environment Variables

Population density is positively associated with dockless trip density for all cities. Employment density is only positively associated with trip density in Los Angeles, NYC area and D.C., insignificant in Detroit and Louisville and negatively correlated in Chicago. Considering that the Central Business District in Chicago did not allow for dockless vehicles at the time, this finding makes sense. Job and household entropy, road network density, working age population within 45 minutes of auto travel time, and transit service frequency were generally associated with higher trip rates. In the NYC area, the sign for working age population is negative, likely because the densest parts of NYC (Manhattan, Bronx, Brooklyn, Queens) did not have access to dockless bicycles at the time. Parks were associated with lower trip densities in Los Angeles, NYC area, and Louisville. Census related transportation statistics (% of people who drove to work alone and % of people with two or more vehicles) were not significant in Louisville. Percentage of people with two or more cars was negatively associated with trip density in Los Angeles, D.C., the NYC area, and Detroit. The presence of fixed transit in a CBG was associated with higher trip density in D.C. and Chicago.

Socio Demographic Variables

Once spatial dependencies are accounted for, we find that much of the socio-demographic variables are absorbed by the lag or error value. The percentage of young people tends to be associated with higher trip density particularly in Louisville, Los Angeles, and D.C. Higher minority populations are only associated with fewer trips in Los Angeles, D.C., and Louisville (effect size of 0.5%, 0.4%, and 1.3% decrease for a 1% increase in minorities). In the NYC area in particular, none of the socio-demographic or economic variables are significant indicators of higher trip density.

Socio Economic Variables

The higher poverty rate is only associated with fewer trips in Los Angeles and Detroit. The effect size is rather small, with a 1% increase in CBG poverty rate associated with a 0.5% and a 1.2% decrease in CBG trip density in Los Angeles and Detroit, respectively. Median household income is not a significant indicator of trip density in any of the cities.

Duration of Trips

An analysis of the duration of trips was conducted (results in the supplementary material). When including all cities combined **(Table 19)**, the results showed that built environment variables were significant in determining the length of a trip. Parks were associated with longer trips while having a trip end within 0.1 mile of a fixed transit station was associated with shorter trips. Trips ending in younger populated areas were associated with shorter, albeit more frequent, trips. Weather did not appear to significantly impact trip duration. Scooter were associated with shorter trips than bikes. Weekends were associated with longer trips. Trip duration was longest during the 3pm-6pm time range. On the other hand, minority and impoverished areas were not associated with differences in trip duration. When separate models are compiled for each city, we find differences in term of how variables interact with trip duration.

Discussion and Conclusion

This study sought to analyze how socio-demographic and economic variables impact shared micromobility usage at a multi-city scale. A spatial regression analysis was performed for six cities across the U.S. based on public API data availability from vendors for dockless bikes and scooters. We found that built environment variables were strong predictors of trip density in a CBG. Generally, the percentage of parks in a CBG and the percentage of households with at least two cars were associated with fewer trips while population, employment & road density, household and employment entropy, presence of fixed transit, and frequency of bus transit were associated with more trips.

The link with socio-demographic and economic variables was less clear. CBGs with higher proportions of young people tend to use micromobility more often. Percentage of minorities were negatively associated with trip density in Louisville, Los Angeles, and D.C. and insignificant in Chicago, the NYC area, and Detroit. Even in cities where there was statistical significance, the effect size was small: 0.5%, 0.4% and 1.3% decrease in trips for a 1% increase in minorities for Los Angeles, D.C., and Louisville, respectively. Median household income was insignificant in all of the cities. However, the percentage of people under the poverty line showed significance in Los Angeles and Detroit, with an effect size of 0.5% and 1.2% decrease in trips for a 1% increase in persons under the poverty line, respectively.

In the NYC area specifically, none of the socio-demographic or economic variables proved statistically significant. There is a special case to be made as the bikes were likely subject to different rules since the four towns spanned three different counties. Additionally, the bikes were constrained only to those four towns and excluded from much of Queens, Brooklyn, the Bronx, and Manhattan. The towns are also not well served by transit compared to the aforementioned boroughs. More analysis is needed to conclude that equity of micromobility access is or is not widespread in the NYC area. Similarly, Chicago had a micromobility pilot at the time of analysis that did not provide access to micromobility in the core of the city. Therefore, usage is likely to be very much impacted by that constraint: if people wanted to get from a residential area to the central business district, they would not be able to do so with dockless micromobility.

In the other cities, we find that access of dockless micromobility could be made more equitable. Louisville and Detroit had the highest effect size for percentage of minorities and percentage below the poverty line, respectively. More effort can be placed to provide micromobility in underserved areas. The effect size in D.C. and Los Angeles was smaller, yet still statistically significant.

We recommend that local agencies and vendors work together to increase access to micromobility in impoverished areas and areas with underserved minorities. While most cities already mandate a certain number of vehicles be available in underserved areas, this analysis suggests that it may not be sufficient. For instance, D.C. local transportation mandates that a certain number of bikes be available in each ward in order to promote equity. Yet, minority areas were still associated with fewer trips. Detroit also mandates that vehicles be available in specific parts of its city, yet poverty rate was associated with fewer trips there. Rebalancing in underserved communities and providing low-income pricing are two options that would promote the access and usage of micromobility.

Limitations and Future Work

This study acknowledges several limitations. API data is useful and proved to be spatially representative of true micromobility movements. However, API data were not available for more than two vendors in each city and requires further analysis in terms of weighing the data to compare results across cities. Moreover, the data were not spatially representative for trip duration when compared to Louisville's official micromobility trips. The data were scraped every minute, which inadvertently rounds trip ends up or possibly misses trips. Some vendors provide API data in real time, although many provide it at 60 second to up to 300 second intervals, limiting the user in how often they can scrape data. Independent variables, such as socio-demographic, economic and built environment variables, were available at the CBG scale at the smallest scale which have an average population of around 1000-1500 people. The only interpretations that could be made were therefore at the neighborhood level. Moreover, there was no comprehensive data source for bike lanes and bike infrastructure at the national level, a variable likely to impact micromobility usage spatially [142]. Furthermore, rebalancing and availability of vehicles, which significantly impact how micromobility is used, were not included in this study due to lack of data and issues of endogeneity. Trip ends were used throughout this analysis to partly correct for user choice, but there are possibilities where trips could not be made due to the unavailability of a bike. Future work should focus on analyzing how policies impact usage of micromobility, in order to promote equitable access of micromobility.

Chapter 5: Conclusion and Remarks for Future Work

Synthesis of Contributions

This dissertation sought to analyze the environmental, economic, societal and sustainability impacts of shared micromobility. In a time where transportation is one of the leading sources of greenhouse gas emissions, innovative research is needed in order to help meet climate change reduction related targets. Moreover, transportation is instrumental in providing opportunities, in terms of jobs, health care, food, etc. Therefore, ensuring that transportation is not only sustainable, but also equitable, is an important part of transportation research. All three studies used data from open sources or publicly available API data. The first study analyzed access and mode shift. The second study examined environmental and temporal determinants of micromobility. The third study explored equitable access in micromobility.

The first study (Chapter 2) established a link between bikeshare usage and public transit usage when public transit is unavailable. The inquiry was "How do transit disruptions impact bikeshare usage?" An autoregressive Poisson time series model was conducted and found that close to 1,000 additional bikeshare rides were taken during three separate transit disruptions. Transit disruptions provide a unique opportunity to understand alternatives for transit riders and how travel decisions are made, both of which are crucial for drafting future transportation policies. I recommend that policy makers and planners (1) consider bikeshare station capacity during a transit disruption. Station capacity is much lower than the number of people who have to switch modes because of transit disruptions; (2) account for proximity of rail and bikeshare stations - several surges did not qualify for this study because bikeshare was further than 0.25 mile from a station and we considered that to be too far to be a viable alternative to transit; and (3) examine rail station spacing - some stations had bikeshare available at both stations, but the rail spacing exceeded 3 miles.

The second study (Chapter 3) examined the environmental and temporal determinants of micromobility. One of the objectives of the study was to look at how micromobility could compete with other modes. I found that (1) weather was less of a disutility for scooter users than station-based bikeshare users, which makes scooters more competitive with cars and public transit. Moreover, (2) all micromobility users were sensitive to gas prices. This indicates a possible competition with car users and a promising shift towards low-carbon mobility. Dockless scooter-share could cut costs in inclement weather-related infrastructure typically associated with biking while also being more environmentally friendly than auto-travel and public transit.

The third study (Chapter 4) addressed equity of usage of micromobility in six U.S. cities. Built environment data, socio-demographic data, and socio-economic data were used as independent variables for the model. After addressing spatial dependencies and controlling for built environment and socio-demographic variables, I found that there still remained inequities in usage in high-poverty and high-minority areas. These findings were especially pronounced in cities with well-established dockless micromobility systems, such as Los Angeles, D.C., Louisville, and Detroit. Chicago and the NYC area, which had pilot programs, did not show a significant association between minorities or poverty and trip density. I recommend that special attention be paid in underserved areas with respect to how bikes and scooters should be deployed.

While micromobility is sustainable and has the potential to compete with more established modes of transportation, like public transit and auto travel, there still remained inequities in access among underserved communities. This dissertation served as a starting point to explore the potential of micromobility.

Limitations

This dissertation acknowledges several limitations: lack of survey data, missing controls, and supply & demand endogeneity in micromobility. First, most of the analyses were conducted at an aggregated level and conjectures could be made only at the neighborhood level. Existing survey data show that users of micromobility tend to be higher educated, white, middle-age, and higher income [18]. In the context of equity, this shows that usage is unequal among the very people who are likely to be part of underserved communities. Surveys would be beneficial in assessing progress of policies aimed at improving equity of usage in underserved communities.

Several controls in the studies are missing due to data unavailability. Bikeway infrastructure, which is evolving rapidly, is available in only select cities. D.C. is one such city that provides that data and it would be interesting to analyze how the infrastructure impacts trip making. Several studies have found that bikeway infrastructure correlates positively with bike trips [74, 142]. Additionally, information on tourism and users who were tourists was unavailable in any of the studies. This study is important when considering regular users of micromobility. Studies have shown that dockless micromobility users behave more like recreational users than like commuters. According to a Lime survey, around 18% of respondents reported riding the scooter in cities they were visiting [22]. Crime and safety data can also influence usage of micromobility. This is closely tied to the availability of bike infrastructure, which is not available equally everywhere. People may not feel safe riding alongside cars. While scooters have not been shown to be more dangerous than other forms of transportations, many people perceive micromobility to be unsafe which in turn affects their travel behavior.

The third limitation is tied to supply of micromobility. Vendors largely decide how many, when, and where scooters are allocated. Therefore, usership of scooters is dictated by the supply available. Data on where micromobility is rebalanced is rarely available and is a common issue in micromobility research. Vendors seek to maximize profit and place vehicles where they are more likely to be used. Departments of transportation usually require vendors to have vehicles available in low-income areas and to have low-income pricing available although that is not universal, and it does not ensure equity of outcome.

Future Directions

Shared micromobility has grown exponentially since it made its debut in the U.S. in 2010. However, research in usership of shared micromobility and its potentials are still understudied compared to other transportation areas. I propose the following research directions: (1) micromobility and moving away from the car. What is the role of micromobility in reducing how many miles traveled people drive? There is a lack of data and surveys available to address this question. However, efforts should be allocated to understand if and how micromobility impacts vehicle usage, particularly among younger populations.

(2) micromobility and equity. Chapter 4 only scratches the surface of equity issues in transportation access. Fewer trips are occurring in underserved communities, but it is not clear whether it is because supply is limited (and not merely because underserved communities are not using the service). API data could help address this question, although working with vendors and local agencies would provide a better idea of how micromobility supply can help improve access. Another important topic is transit-induced gentrification. There is evidence that public transit has led to gentrification issues [143-148]. Bike lanes improve street design and contribute to gentrification as well [149, 150]. This issue is one that should be researched further in relation with shared micromobility.

(3) Micromobility and public safety. This larger topic has not been addressed by this dissertation but is an important next step in understanding how micromobility can have a long-term future. Micromobility is a relatively safe form of transportation when used safely (i.e., use of helmet, obeying street signs) and when dedicated infrastructure is available. On the other hand, micromobility has also been subject to theft and vandalism [151]. This has consequences on how vendors deploy their vehicles. Such actions can also impact vehicle equity and limit access in underserved areas. This understudied topic is worthy of more research and collaboration with vendors and local agencies.

Supplementary Material

Chapter 2

Figures 12-14: The following sets of plots display the autocorrelation function of (1) the dependent variable, (2) the residuals of the non-lagged Poisson regression model and (3) the residuals of the autoregressive Poisson model described in the *Analysis & Results* section in chapter 2. The lags of the first thirty days are shown for each surge in the three sets of tables. Each column above the dashed threshold is considered to be statistically significant. The first column is always 1 since it is the autocorrelation value of a term with itself. For the first set of plots, we find a strong weekly pattern, with every seven term being the highest but slowly decreasing as time goes on. For a particular Monday, this means that the Monday of the week before will have a stronger autocorrelation than the Monday that happened two weeks before and so on. What is not observed in the plots is the yearly seasonality. Over the course of the year, the weekly pattern remains but autocorrelation becomes statistically insignificant after about 3 months. It becomes statistically significant with a small negative autocorrelation at about the 6-month mark (although including a 6-month lag term did not significantly improve the model). Finally, the lags once again become significant and positively autocorrelated after 11 months, peaking at about one year. This pattern is expected in seasonally influenced data. In conclusion, we observe in **Figure 12** that there is a strong autocorrelation in weekly bikeshare activity.

Figure 13 displays the residual autocorrelation for the Poisson model. After controlling for weather and weekend patterns, residual autocorrelation is low, although still statistically significant over the course of the 30 lag terms. As a result, the model is not the best fit for the data. **Figure 14** shows the residual autocorrelation for the Autoregressive model with 1-day, 1-week and 1-year lag terms. Because a time series is used, the x-axis now represents the day as a fraction of 365 days (such that 30/365 is 0.082). For all three surges, the autocorrelation function plots show that the model is better able control for autocorrelation in the residuals than the general Poisson model.

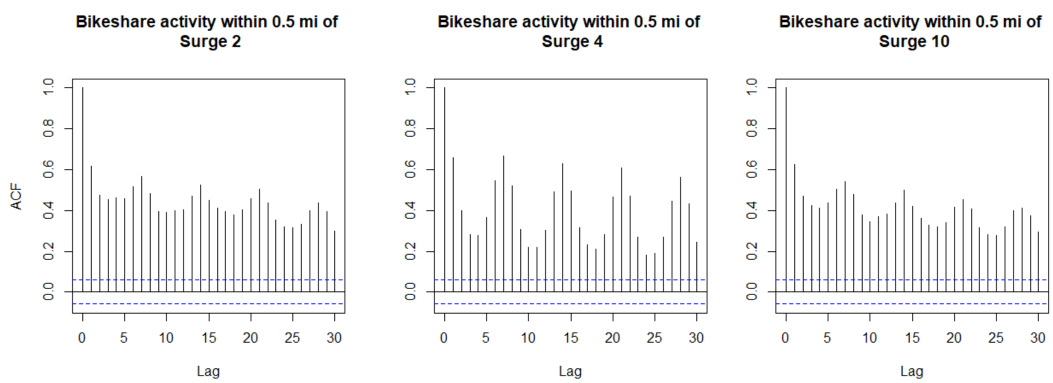


Figure 12: Autocorrelation Function Plots for Dependent Variable (daily bikeshare activity)

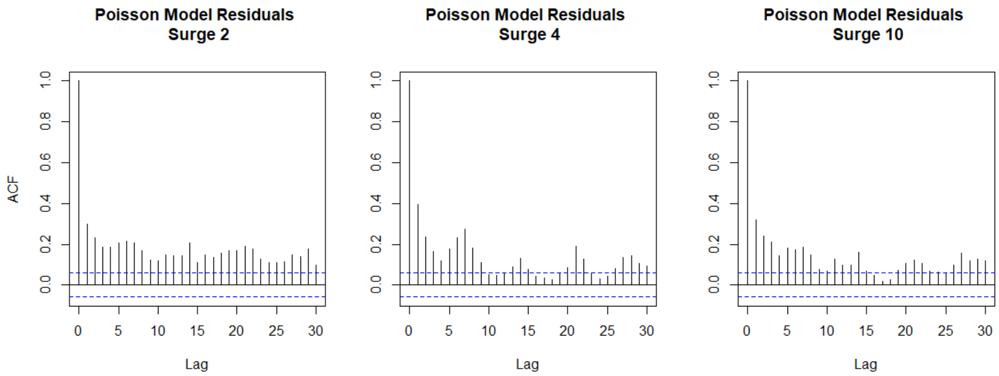


Figure 13: Autocorrelation Functions Plots for Residuals of Poisson Model

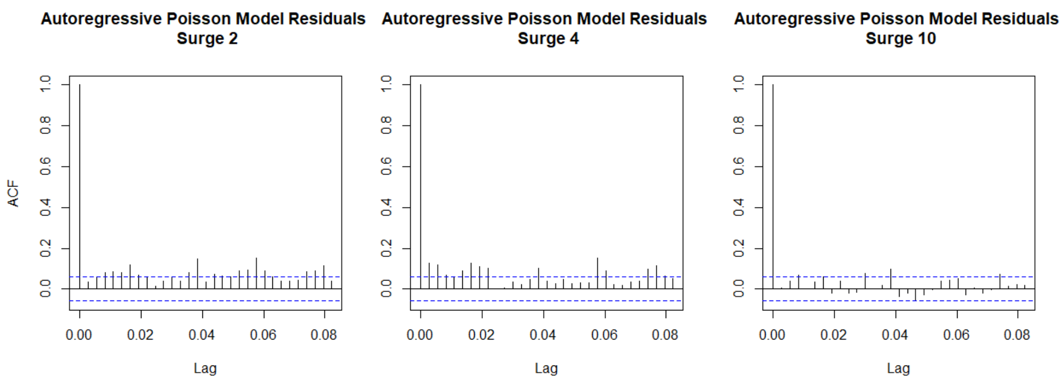


Figure 14: Autocorrelation Function Plots for Residuals of Autoregressive Poisson model

Figure 15 displays the kernel density estimation in the change in ridership for each time period and each surge. The blue areas represent lower density estimates of trip increases while the red areas represent the greatest increases in trip ridership change. This is a decomposition of **Figure 5** in Chapter 2 of the dissertation. A comparison of time can be observed vertically for each surge while horizontally, each surge can be compared for a specific time period. As in **Figure 5**, the bottom quintile of each estimation is excluded in order to visualize the top 80% of probability density estimates in increases in trips.

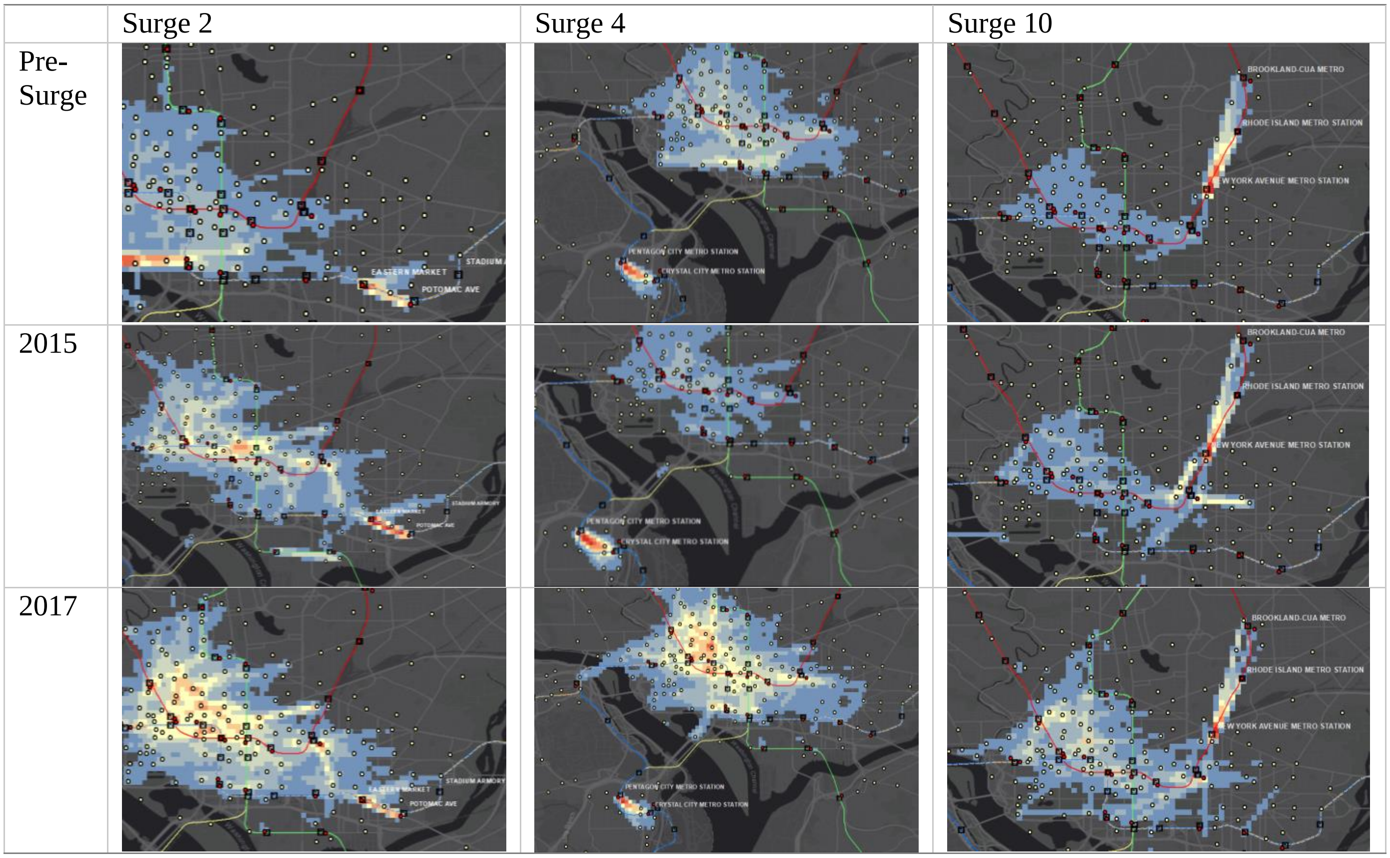


Figure 15: Kernel Density Estimation of change in ridership, decomposed by surge and by time period

Chapter 3

The software R was used to convert API data into a tidy dataset as shown in **Figure 16**. Roughly half a million individual scrapes took place during the 6-month period that data were collected. Since there was no publicly available package for the conversion, I created my own set of functions in R.

from


```
{"last_updated":1580756738,"ttl":0,"data":{"bikes":
[{"bike_id":6148537,"lat":38.92517,"lon":-77.05559,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
{"bike_id":6133986,"lat":38.91026,"lon":-77.04222,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
{"bike_id":9597475,"lat":38.88356,"lon":-77.02517,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
{"bike_id":1152495,"lat":38.89533,"lon":-76.94889,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
{"bike_id":9127426,"lat":38.88639,"lon":-77.01636,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
{"bike_id":7386651,"lat":38.93611,"lon":-77.02257,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
{"bike_id":5114540,"lat":38.90542,"lon":-77.05913,"vehicle_type":"scooter","is_reserved":0,"is_disabled":0},
```


to

TripID	bike_id	vehicle_type	StartDateTime	EndDateTime	durationmin	startlat	endlat	startlong	endlong	OD Dist MIL	ODspeedmph
AM5TQFB	AM5TQFB	scooter	6/17/2019 11:47	6/17/2019 11:48	0.5	38.898	38.897	-77.034	-77.034	0.0509	6.1138
HHSTSQC4	HHSTSQC4	scooter	6/17/2019 11:47	6/17/2019 11:48	0.5	38.901	38.901	-77.043	-77.042	0.0543	6.5153
XIVHZXJSH	XIVHZXJSH	scooter	6/17/2019 11:47	6/17/2019 12:25	37.5	38.897	38.883	-77.010	-77.032	1.5416	2.4644
COXEWEI5	COXEWEI5	scooter	6/17/2019 11:48	6/17/2019 11:51	3.4	38.896	38.896	-77.029	-77.027	0.0870	1.5504
PB7UILBN	PB7UILBN	scooter	6/17/2019 11:48	6/17/2019 12:10	22.0	38.892	38.890	-77.028	-77.015	0.6949	1.8937
32QRZELP	32QRZELP	scooter	6/17/2019 11:48	6/17/2019 12:01	12.9	38.860	38.863	-77.049	-77.059	0.5902	2.7382
7CCBJDEF	7CCBJDEF	scooter	6/17/2019 11:48	6/17/2019 11:51	3.4	38.843	38.842	-77.052	-77.051	0.0429	0.7689
H5NYWZ6	H5NYWZ6	scooter	6/17/2019 11:48	6/17/2019 11:58	10.4	38.850	38.864	-77.051	-77.049	0.9951	5.7227
2FXH3YCG	2FXH3YCG	scooter	6/17/2019 11:48	6/17/2019 11:51	2.7	38.915	38.915	-77.046	-77.047	0.0300	0.6711

Figure 16: Data Processing

This supplementary section will describe the important functions created to process data. The functions were also used in Chapter 4. The two main functions used were Gz2json2df and df2trips. For the first function, the input is a path (folder) that contains "*.json.gz" files. The output is a single data frame where each row is a point (not a trip). One month of data typically implicates millions of points. **Figure 17** displays the data frame format (output) of the function.

```
> head(mydata)
    bike_id      lat        lon is_reserved is_disabled lastupdate
1 MM69-AM83 25.763348 -80.193368           0           0 1580706462
2 RN59-TK95 25.784762 -80.191643           0           0 1580706462
3 IF62-QJ35 25.771518 -80.190175           0           0 1580706462
4 GI39-CX36 25.773257 -80.193772           0           0 1580706462
5 PG13-WF91 25.772743 -80.187543           0           0 1580706462
6 FJ81-CF48 25.780235 -80.189288           0           0 1580706462
```

Figure 17: Output of function Gz2json2df()

The second function converts the point data to trip data. The input is the data frame from the initial function. The function sorts the data by bike ID and time in order to find trip starts and ends. It also filters out all intermediate points in which the bike is reserved and all “trips” where the bike did not move. Moreover, trips under 2 minutes and over 90 minutes are filtered, trips that are shorter than 0.2 miles, and trips that are at high speed (potentially rebalanced bikes) are removed as well (>16mph). The resulting table looks like the bottom table in **Figure 16**.

Chapter 4

1. *Data Quality Check: Time Correlation Between Cities*

Table 16 displays the time and day correlation between each city. We analyze the number of hourly trips depending on the day of the week. For the most part, cities behave the same way, reinforcing that the data quality is good. Miami, FL, however; does not seem to have the same pattern. After further analysis, we believe that the data collected for Miami were not reliable and thus exclude Miami from the model analysis. **Figure 18** provides a visual of the trend in daily activity in dockless micromobility usage by city.

Table 16: Time Correlation between Cities (Average Hourly Trips per day)

Time and day of week correlation	DC	LA	CHI	NYC	DET	LOU	MIA
DC	1						
LA	0.9561522	1					
CHI	0.8975162	0.9198622	1				
NYC	0.8892927	0.9339615	0.884817	1			
DET	0.8606317	0.9027525	0.8905106	0.9059623	1		
LOU	0.8477719	0.8539283	0.85779	0.8004512	0.837465	1	
MIA	0.5500931	0.5760744	0.4643714	0.626883	0.5899252	0.3805631	1

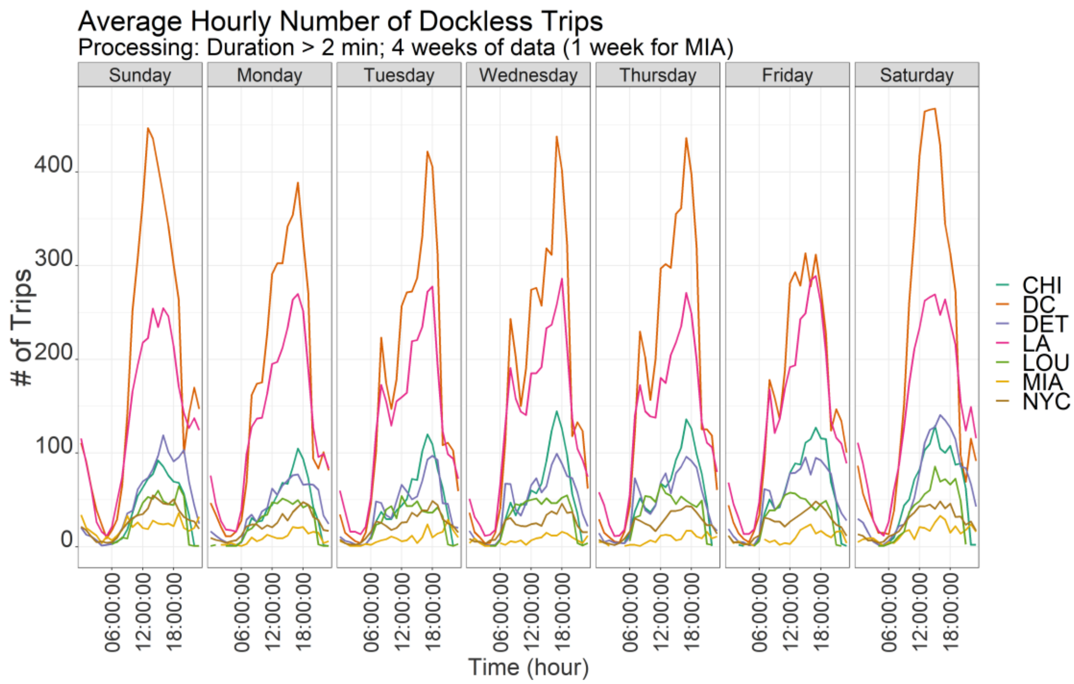


Figure 18: Average Hourly Number of Trips in 7 Cities (unweighted for various vendors)

2. OLS Regression Modeling

A log-linear OLS regression model is performed for the six cities as specified in **Eq. (6)**:

$$\ln(y) = \beta_0 + \beta_1 x$$

The dependent variable is the log transformed trip density in each census block group. The trip density is log transformed because of its strong right skew (between 3.1 and 8.4 for the six cities) and because the residuals of the un-transformed models all have a right skew (between 0.76 and 7.13). When the dependent variable is transformed, the skew of the residuals ranges between -0.64 and 0.57. The variance inflation factor is used to ensure that no variable has a VIF above

5. Hence, the variable "% of population with no car" is omitted in the Detroit and Louisville models because of high VIF.

We tested for spatial autocorrelation (Moran's I) by *k* nearest neighbor (with k=1-10), by distance (with d = 3.3 km) and by contiguity (Queen's and Rook's) in the dependent variable and the OLS model residuals to decide whether a spatial lagged model is appropriate. Due to the variant nature of the cities and their CBG size, the contiguity method proved to be more appropriate than neighbor or distance methods. The dependent variable is spatially autocorrelated for all six cities regardless of the spatial weights method employed. The model residuals are spatially autocorrelated in Los Angeles, Chicago and Detroit when using k nearest neighbors or distance and spatially autocorrelated for all cities when using contiguity method.

Table 17: OLS Regression Results

	Dependent variable:					
	Log (trip density per CBG)					
	LA(1)	DC(2)	CHI(3)	NYC(4)	DET(5)	LOU(6)
Gross Population density (people/acre)	0.019***	0.009***	0.018***	0.012***	0.049***	0.078**
	(0.002)	(0.002)	(0.004)	(0.003)	(0.016)	(0.031)
Gross employment density (jobs/acre)	0.005***	0.003***	-0.012***	0.016***	0.007	-0.013
	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.008)
Employment and Household Entropy	0.687***	0.861***	0.469**	-0.058	1.311***	0.083
	(0.189)	(0.176)	(0.211)	(0.283)	(0.396)	(0.392)
Aggregate frequency of transit service within 0.25 mi of CBG per hour	-0.0001	-0.0001	0.002*	0.009***	0.005***	0.006***
	(0.0002)	(0.0003)	(0.001)	(0.002)	(0.001)	(0.002)
Aggregate frequency of transit service per square mile	-0.00001	-0.00000	0.0001	-0.0002**	0.0002*	0.001***
	(0.00001)	(0.00002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)

Total road network density	0.046***	0.024***	-0.007	0.024***	0.080***	0.039**
	(0.005)	(0.005)	(0.008)	(0.009)	(0.016)	(0.018)
Working age population within 45 minutes auto travel time (in 1000s)	0.001***	0.019***	0.006***	-0.004***	-0.002	0.036***
	(0.0002)	(0.002)	(0.001)	(0.0004)	(0.002)	(0.007)
%[6] of CBG that is local, state, or national Park	-0.0094	-0.0059*	0.0067	-0.013***	-0.004	-0.015
	(0.006)	(0.003)	(0.006)	(0.004)	(0.014)	(0.014)
% of population that drives to work alone	-0.020***	-0.014***	0.002	0.005	-0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
% of the population with no car	0.003	-0.003	0.002	0.008	Omitted	Omitted
	(0.005)	(0.004)	(0.004)	(0.005)		
% of population with 2 or more cars	-0.030***	-0.016***	0.001	-0.010**	-0.023***	-0.005
	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.008)
Number of fixed transit stations in CBG	0.112	0.304**	0.339***	0.078	N/A	N/A
	(0.165)	(0.123)	(0.128)	(0.168)		
Area of CBG in sq mi	-0.837***	-0.652***	-3.916***	-2.368***	-0.895*	-0.111
	(0.105)	(0.164)	(0.827)	(0.295)	(0.509)	(0.240)
% Age 18-21	-0.003	0.019***	0.017*	-0.009	0.011	0.060***
	(0.006)	(0.004)	(0.009)	(0.017)	(0.014)	(0.011)
% Age22-29	0.025***	0.023***	0.017***	0.019**	0.029***	-0.0001
	(0.005)	(0.004)	(0.006)	(0.009)	(0.011)	(0.012)
% Age 30-39	0.022***	0.028***	0.033***	0.008	0.001	0.024*
	(0.005)	(0.005)	(0.007)	(0.010)	(0.013)	(0.014)
% Under the poverty line	-0.012***	0.00655	-0.01**	-0.012**	-0.009	0.005
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
% of Black/African American or	-0.018***	-0.010***	-0.005**	-0.004*	-0.010***	-0.014***

[6] The percentages in this model range between 0 and 100. Therefore, where the coefficient beta < 0.1, the coefficient represents approximately the percentage (multiplied by 100) change in trip density for a 1% change in each variable.

Hispanic/Latino						
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Median Household Income (in 1000s)	0.003**	0.004***	0.001	-0.005***	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)	(0.005)
Constant	-9.770***	-17.622***	-14.193***	-7.602***	-12.936***	-19.710***
	(0.488)	(0.683)	(0.738)	(0.495)	(0.988)	(1.377)
Observations	1,423	583	573	281	248	211
R^2	0.517	0.833	0.520	0.730	0.649	0.730
Adjusted R^2	0.510	0.828	0.503	0.710	0.623	0.706
Residual Std. Error	1.272 (df = 1403)	0.851 (df = 563)	0.903 (df = 553)	0.838 (df = 261)	1.239 (df = 230)	1.101 (df = 193)
F Statistic	79.039*** (df = 19; 1403)	148.330*** (df = 19; 563)	31.470*** (df = 19; 553)	37.075*** (df = 19; 261)	25.055*** (df = 17; 230)	30.676*** (df = 17; 193)
Note:	Number in parenthesis represents the standard error *p<0.1; **p<0.05; ***p<0.01					

The models above control for built environment variables, socio-demographic variables, and socio-economic variables. The findings are summarized below. We interpret the effect size for continuous variables, where β is the coefficient, with the following formula **Eq. (7)** [65, 66]:

$$\%\Delta y = 100 * (e^{\beta} - 1)$$

For a one-unit change in independent variable *x*, we expect the relative change in *y* to be the exponent of the coefficient of *x* minus one multiplied by one hundred percent.

Built Environment

Built environment variables and their association with micromobility vary from city to city. This is to be expected as the cities vary widely in terms of their populations size and makeup (as outlined in **Table 14** in the manuscript). We do find that for all six cities, population density is positively associated with trip density. Driving to work or owning at least two vehicles was associated with fewer trips while an increased number of fixed transit station, higher frequency of bus service, and percentage of people with no vehicle were associated with higher number of trips in all cities. In particular, Louisville sees an important increase in trips with increased transit service; it is the only city in this study to not have any fixed transit available. Employment and housing entropy, or diversity, is a positive and significant factor for Los Angeles, Chicago, D.C., and Detroit, highlighting the importance of mixed-use development for sustainable transportation. The NYC area is a special case in that the scooters are unavailable in the highest job density areas of NYC, namely Manhattan, Brooklyn, much of Queens, and the Bronx.

Socio-Demographic

Areas with younger populations are associated with having higher densities of trips. The variables are broken down into 18–21-year-old (high percentage indicates college campuses) and 22-29 years old which are both positively associated with higher trips. Louisville, KY, home of University of Louisville, has the strongest association of trips and 18–21-year-olds with 6% increase in trips for a 1% increase in 18–21-year-olds. Los Angeles's UCLA campus has its own bikeshare system and the NYC area does not have any major universities. Detroit's Wayne State College's population does bring many trips on campus, although not enough to overcome the large number of trips from 22–29-year-olds. This is in line with previous findings [111]. Moreover, areas with higher concentrations of under-represented minorities (Black/African American and Hispanic/Latino) have lower trip densities. Remarkably, this is the case for all six cities. A 1% increase in minorities in a CBG is associated with a 0.4-1.8% decrease in trips. This is an important finding as it highlights the need for equitable access.

Socio-Economic

We found that income and income quartiles did not have practical significance in determining the usage of micromobility at the CBG level. On the other hand, we found that poverty rate is negatively associated with trip density in three of the cities (LA, Chicago, and NYC area) and insignificant in the other three. This mixture of findings depending on the city is similar to what other studies have found: low-income regions in Austin, TX have been found to generate more trips while regions in Minneapolis have been insignificant [93].

3. *Spatial Model*

a. *Lagrange Multiplier Test*

We use the Lagrange Multiplier test to report the estimates of five statistics for spatial dependence in our OLS models [152-154]. The spatial weights are based off of Queen's Contiguity. The results supplement those of the AIC test. LA and D.C. report significant values for all of the tests and thus it is not clear solely from looking at these results that one spatial model is better than another (**Table 18**). Chicago does not report statistical significance for the RLMerr statistic, suggestion that error dependence is not an issue in the presence of a missing lag variable. In this case, a lag model is more appropriate than an error model. Detroit and Louisville do not report a statistically significant LMlag or RLMlag statistic, suggesting that the spatial error model is more appropriate.

Table 18: Lagrange Multiplier Test

	LA	DC	CHI	NYC	DET	LOU
LMerr (simple LM test for error	1366.3, df = 1, p-value <	216.55, df = 1, p-value <	234.41, df = 1, p-value <	42.711, df = 1, p-value =	76.308, df = 1, p-value <	60.259, df = 1, p-value =

dependence)	2.2e-16	2.2e-16	2.2e-16	6.346e-11	2.2e-16	8.327e-15
LMlag (simple LM test for error dependence)	485.41, df = 1, p-value < 2.2e-16	196.13, df = 1, p-value < 2.2e-16	332.72, df = 1, p-value < 2.2e-16	16.03, df = 1, p-value = 6.236e-05	**0.91283, df = 1, p-value = 0.3394**	**3.2188, df = 1, p-value = 0.0728**
RLMerr (error dependence in the presence of a missing lag variable)	894.48, df = 1, p-value < 2.2e-16	62.332, df = 1, p-value = 2.887e-15	**0.0016265, df = 1, p-value = 0.9678**	27.233, df = 1, p-value = 1.803e-07	76.393, df = 1, p-value < 2.2e-16	57.764, df = 1, p-value = 2.953e-14
RLMlag (missing lag dependent variable in the presence of error dependence)	13.611, df = 1, p-value = 0.0002249	41.916, df = 1, p-value = 9.526e-11	98.309, df = 1, p-value < 2.2e-16	**0.55204, df = 1, p-value = 0.4575**	**0.99747, df = 1, p-value = 0.3179**	**0.72423, df = 1, p-value = 0.3948**
SARMA (LMerr + RLMlag)	1379.9, df = 2, p-value < 2.2e-16	258.46, df = 2, p-value < 2.2e-16	332.72, df = 2, p-value < 2.2e-16	43.263, df = 2, p-value = 4.032e-10	77.305, df = 2, p-value < 2.2e-16	60.983, df = 2, p-value = 5.729e-14

b. AIC Statistic

We supplement the Lagrange Multiplier test with the AIC statistic (**Table 19**). The models that were created for OLS are run as spatial lag and spatial error models for both Rook's contiguity and Queen's contiguity. For all cities aside from Chicago, the model performs best with the lag model. Based on these results, our final models are the spatial error model for LA, D.C., the NYC area, Detroit, and Louisville. A spatial lag model is used for Chicago. Queen's contiguity is used for all models as the spatial weight.

Table 19: AIC of Baseline, Lag, and Error Models for Trip Density

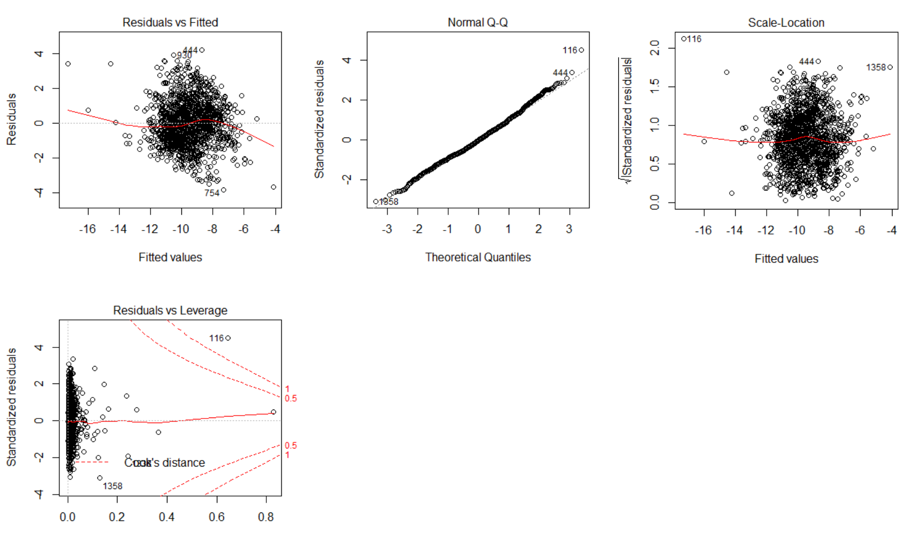
	LA	DC	CHI	NYC	DET	LOU

AIC of OLS model (Baseline)	4744.1	1487.7	1531.4	719.6	829.55	658.54
Lag model Queens Contiguity	4298.7	1302.7	1259.5	706.41	830.67	658.54
Lag model Rook's contiguity	4406.3	1352.1	**1255.2**	705.82	830.94	657.14
Error model Queen Contiguity	**3271.3**	**1253.8**	1282.9	**660.03**	**656.91**	**590.81**
Error model Rook's contiguity	3274.2	1278.2	1287.2	665.28	668.07	594.55

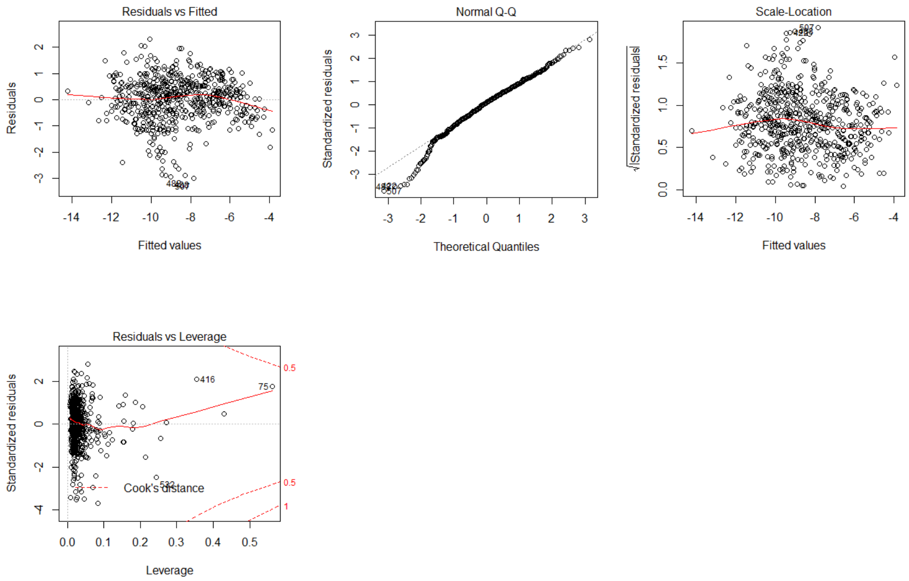
c. Residual Plots and Maps

This section reports the residual plots for the OLS model for each city (**Figure 19**) and the residual maps for the OLS and spatial models for each city (**Figure 20**). In **Figure 20**, we expect that the spatial models help correct the spatial autocorrelation of residuals.

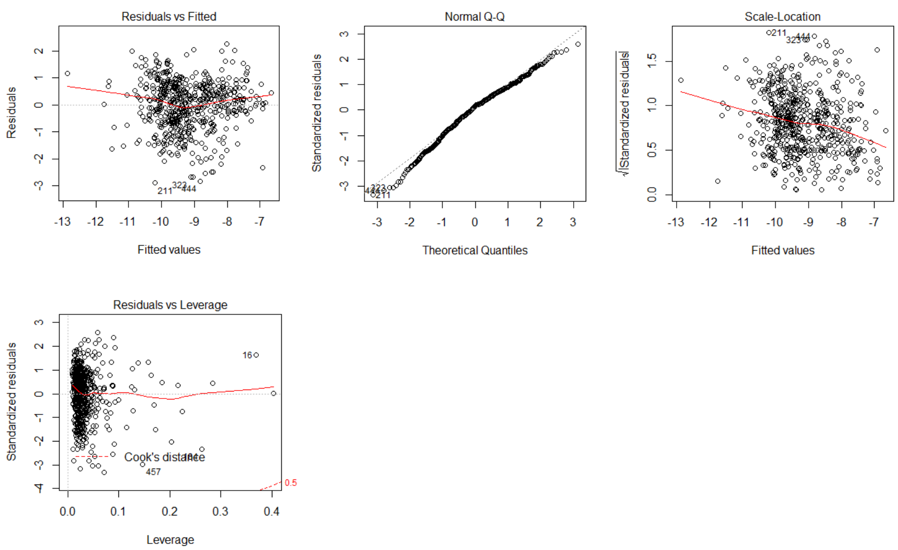
Figure 19: Residual Plots for OLS Models (Trip Density- Log-transformed)



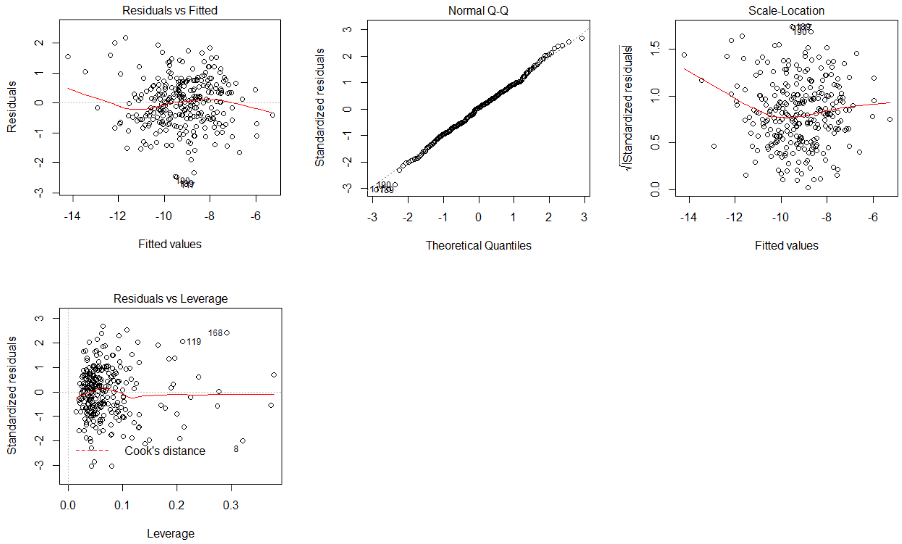
a) Los Angeles Residual Plots



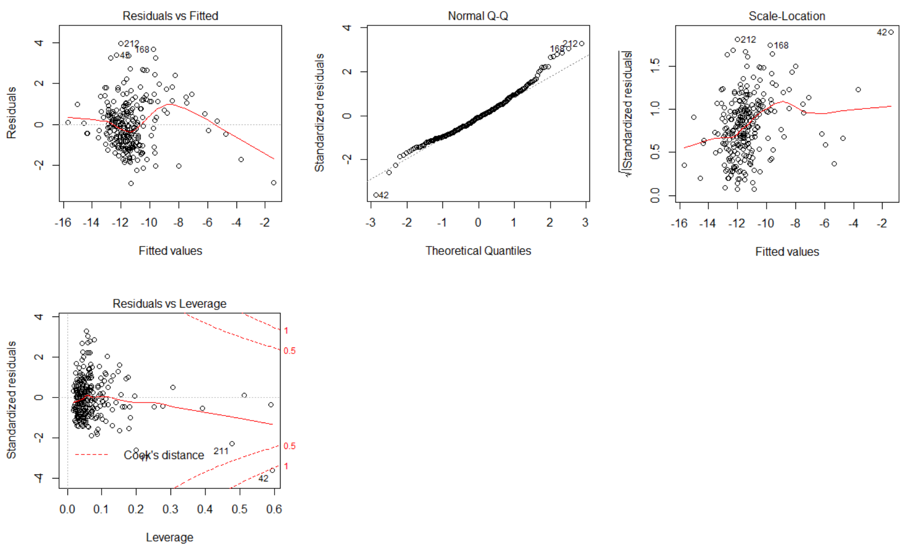
b) D.C. OLS Residual Plots



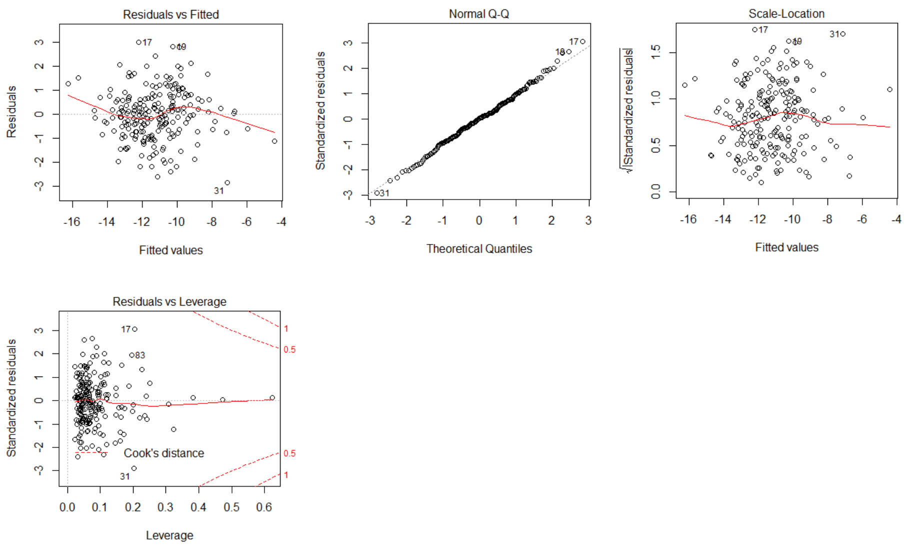
c) Chicago OLS residual Plots



d) NYC OLS residual Plots



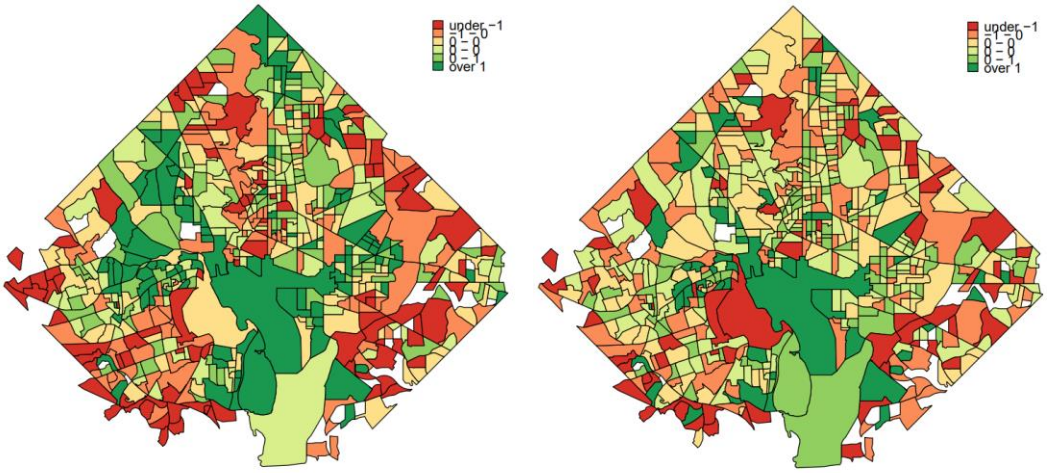
e) Detroit OLS residual plots



f) Louisville OLS residual Plots

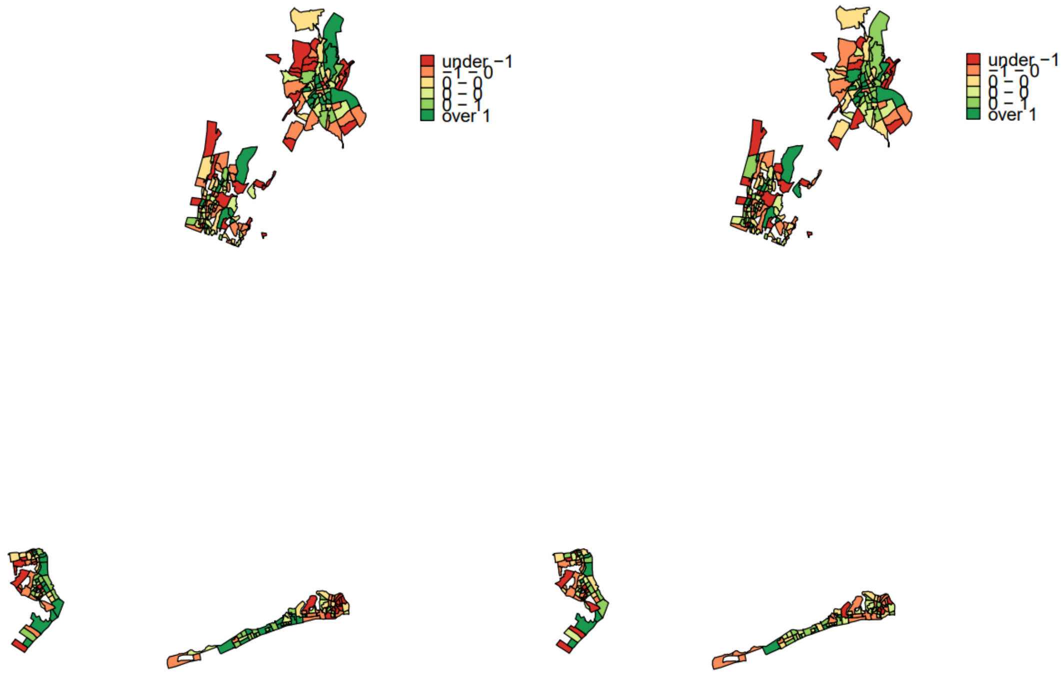
Figure 20: Maps of OLS and Spatial Model Residuals for Trip Density

a) OLS Model Residuals and Spatial Error Model Residuals for Los Angeles, Santa Monica and Long Beach

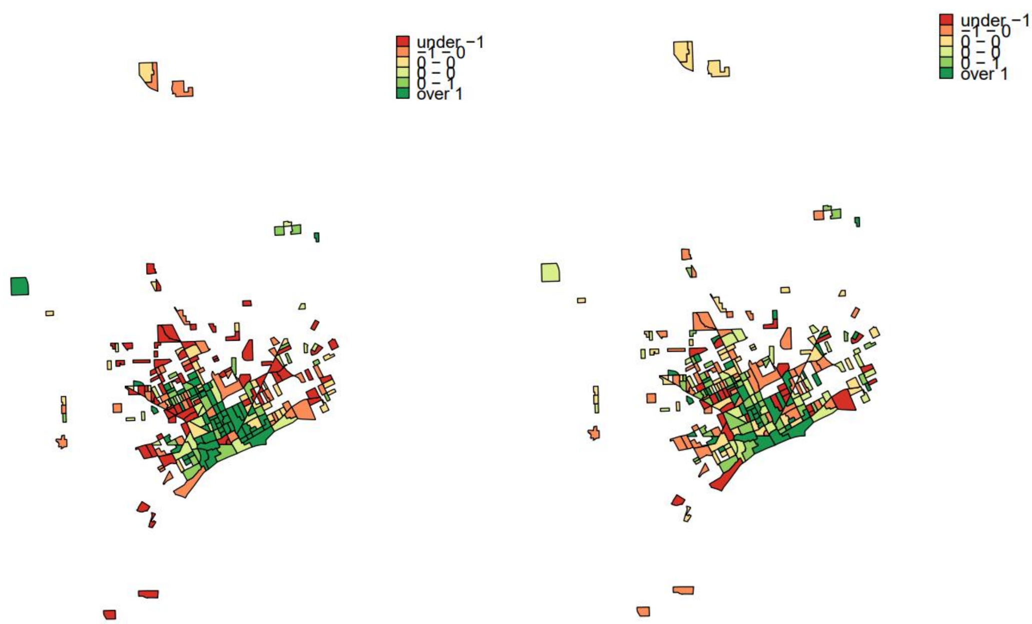


b) OLS Model Residuals and Spatial Error Model Residuals for D.C. and Arlington, VA

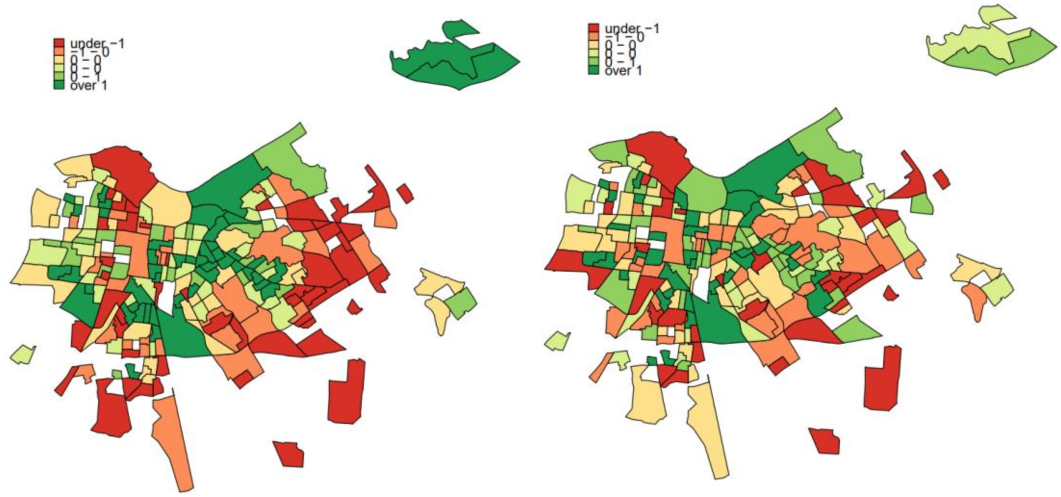
c) OLS Model Residuals and Spatial Lag Model Residuals for Chicago



d) OLS Model Residuals and Spatial Error Model Residuals for NYC area (Staten Island, Rockaway Park, White Plains and Yonkers)



e) OLS Model Residuals and Spatial Error Model Residuals for Detroit



f) OLS Model Residuals and Spatial Error Model Residuals for Louisville

4. *Duration of Trips*

There is interest in understanding how the duration of trip is impacted by built environment and socio-economic and demographic variables. Instead of being at the level of census block group, the data are at the trip level. Each trip is spatially joined with the Smart Location Database (SLD) for built environment attributes, park data, fixed transit stops data, and socio-economic and demographic variables at the CBG level and temporally joined with NOAA's historical weather records [52] and time and day dummy variables. The dependent variable is the duration of trips in minutes, log-transformed. Prior to log-transforming the variable, the skewness of the duration in minutes ranged between 2.3 and 3.1. The skewness of the residuals ranged between 2.34 and 2.96. After log-transforming the dependent variable, the skewness of the log-transformed variable ranged between 0.48 and 0.86 and that of the residuals ranged between 0.44 and 0.77.

We observe that generally, weekend trips are longer than weekday trips, trips that end inside a park are longer, and trips that end near a fixed transit stop are shorter (**Table 20**). In the case of Los Angeles, which has both scooters and bikes in this analysis, scooter trips are much shorter in duration. The data are scraped from API every minute. This means that some trips are inadvertently missed, or trip ends are rounded up to the nearest minute every time. Therefore, the average times here are overestimates. In the ground truth analysis, we saw that the average trip in Louisville was about 1 minute shorter in reality than in our sample. The Wilcoxon test showed that this difference was statistically significant.

Table 20: Duration of trip depending on subset dataset.

	LA		DC		CHI		NYC		DET		LOU	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	Sd
Bike	16.22	14.50					15.71	14.93				
Scooter	11.26	10.36	15.74	14.19	12.71	10.34			13.17	12.44	12.04	12.81
Weekday	14.00	12.96	14.31	13.03	12.30	10.14	14.68	14.13	11.31	11.24	10.84	11.25
Weekend	16.05	14.59	18.73	15.96	13.70	10.75	17.90	16.29	16.89	13.82	15.09	12.62
In Park	22.64	17.68	22.95	17.76	15.63	11.79	22.32	17.60	14.70	13.84	13.99	11.06
Near Transit (0.1 miles)	10.79	10.68	14.25	13.45	11.76	10.07	13.39	13.93	N/A		N/A	
High Minority CBG	13.60	12.62	13.79	11.71	15.46	13.13	15.51	14.72	18.45	15.85	13.48	12.81
High Poverty Rate CBG	14.03	13.07	14.45	12.98	14.06	11.96	15.43	14.49	13.46	12.42	12.49	12.33

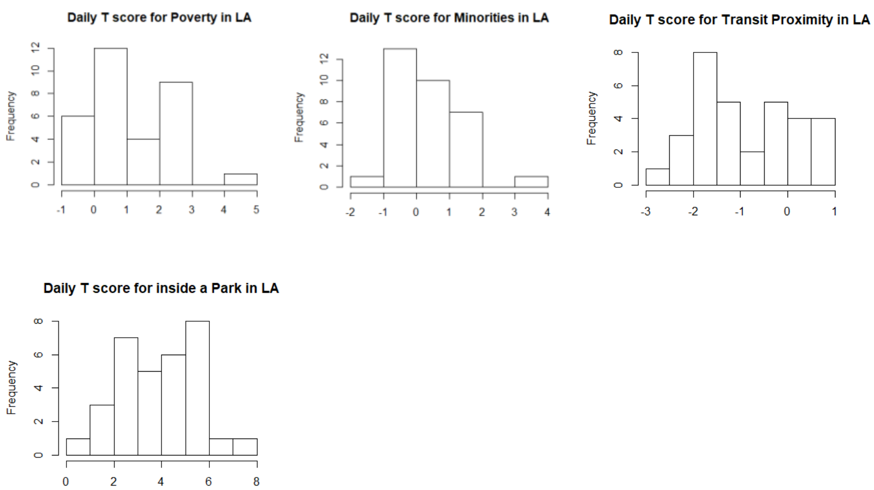
Because of the large dataset size (at least 17,000 records) for each city and the redundancy of trips (non-statistically significant Wilcoxon test in the trip duration from one Monday to the next), we analyze the results of daily and weekly analysis

[66]. Data were collected for 31 days in each of the cities. Some of the variables from the trip density model are omitted because of their high VIF value in the duration model. Percentage of minorities (Hispanic/Latino and African American) and percentage of poverty rate are converted to dummy variables due to high VIF in one of the cities (see Supplementary Material for definitions). Dummy variables will help understand the association with neighborhoods that have high poverty rates or minorities on trip duration. Since the cities differ widely in terms of their socio-demographic makeup, we use the city-specific top 50% quantile to define each dummy variable. For example, in Los Angeles, 50% of the CBGs have at least 39.1% minorities; in contrast, 50% of CBGs have at least 24.4% minorities in Louisville. Similarly, 50% of the CBGs in Detroit have at least 35% poverty rate while 50% of the CBGs in Washington, D.C. have at least 8% poverty rate.

A model is estimated for each day in each city and the t-score for variables of interests are reported below (**Figure 21**). A t-score exceeding |1.96| indicates a confidence interval of 95%. We find that, when controlling for built environment and time of day variables, duration of trips with destinations in high minority or poverty areas are not statistically significantly different from other trips on a daily basis. On the other hand, ending a trip inside a park is strongly associated with longer trips while ending a trip near a transit stop is strongly associated with shorter trips.

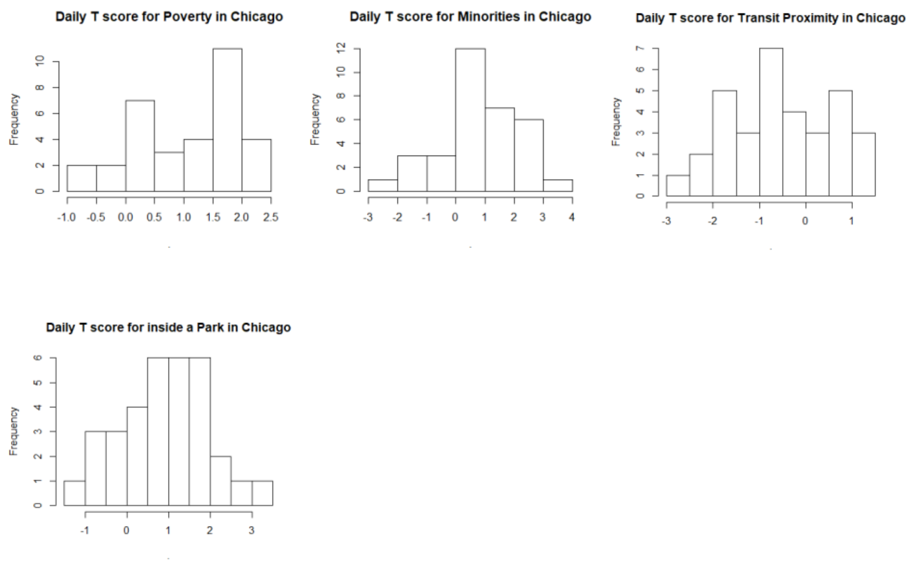
a. Daily Models

Figure 21: T-Score for Daily Models for Los Angeles, D.C., Chicago, NYC area, Detroit, and Louisville for selected variables

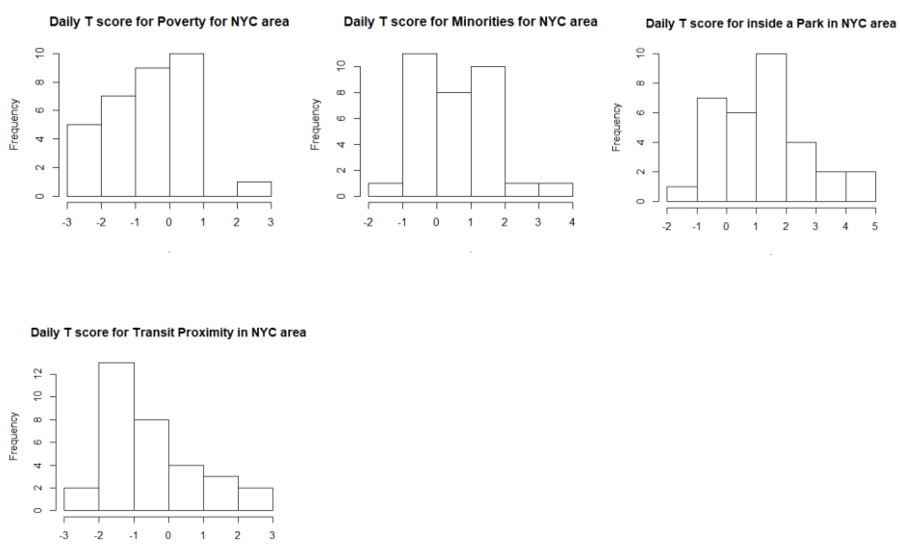


a) Daily T-score for selected variables in Los Angeles

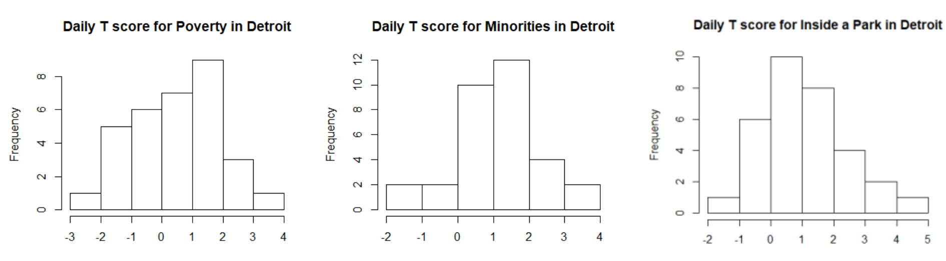
b) Daily T-score for selected variables in D.C.



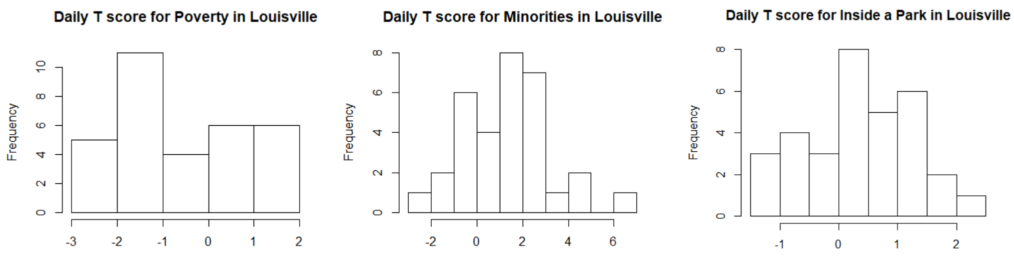
c) Daily T-score for selected variables in Chicago



d) Daily T-score for selected variables in NYC



e) Daily T-score for selected variables in Detroit



f) Daily T-score for selected variables in Louisville

Daily models are not controlling for weather or weekend since the variables are at the daily scale. We estimate models at the weekly scale for all cities combined using a mixed effects model in which the random effect is the city [155]. Overall, we find, much like the daily analysis, that a trip ending in a high minority area or high poverty area is not likely to impact its duration. Generally, temperature and windspeed do not significantly impact the trip length either, while precipitation is statistically significant for three of the four weeks. Built environment variables, on the other hand, have a much stronger association with trip duration. Being inside a park and weekends are associated with longer trips. Population and employment density, entropy, and proximity to fixed transit are associated with shorter trips. Distance to nearest bus transit is not statistically significant meaning that fixed transit generally has a stronger association with trip duration than would bus transit. The table of z-scores for the mixed effects model for each week along with the marginal and conditional R-Squared is shown below (**Table 21**) [156].

b. Weekly Mixed Effects Model for all cities

Table 21: Z-scores for weekly mixed effects model for all cities

	8/25-8/31	**9/1-9/7**	**9/8-9/14**	**9/15-9/21**
(Intercept)	71.12163	62.7873	86.29758	87.28584
Percentage of CBG aged 18-21	-7.88701	-9.73704	-11.1759	-13.9473
Gross residential density (HU/acre)	-28.5516	-27.9831	-27.1248	-27.8301
Housing and Employment Entropy	-13.9411	-11.8005	-13.4071	-11.4806
Trip ends inside a park	25.04844	25.03281	23.6222	22.12171
Working age population within 45 minutes auto travel time (in 1000s)	-15.7393	-13.4368	-13.5664	-13.0265
Distance from population weighted centroid to nearest transit stop (in meters)	0.109767	0.755272	2.617238	2.798715
Total road network density	5.796073	6.074372	4.585048	6.013175
Percentage of CBG with two or more cars	-17.1335	-14.6917	-16.4114	-18.4625
Trip ends within 0.1 mile of fixed transit	-9.65955	-6.87706	-6.38457	-8.18113
Is a scooter (alternative: is a bike)	-24.5916	-24.9379	-25.1793	-26.9879
High % of minority	-1.93512	-3.5138	3.202924	0.771125
High % of under poverty rate	-1.38701	-0.96768	-0.77962	-2.3835
Daily Temperature (F)	1.402176	5.255046	-8.78939	-0.45507
Daily Precipitation (in)	-3.66302	-6.89832	1.353086	-5.69393
Daily Windspeed	-1.82052	-9.88304	0.18413	-1.85016
Is during Weekend	36.37284	27.21076	30.56084	32.69457
t03TRUE	-0.43021	2.998977	-2.2588	0.127413
t36TRUE	-7.12305	-4.67056	-7.95659	-6.1048
t69TRUE	-33.4846	-31.9972	-33.7377	-33.3818
t912TRUE	-21.1234	-18.872	-19.0764	-19.3244
t1215TRUE	-7.85237	-6.37867	-7.50323	-6.91278
t1821TRUE	2.521553	-0.23985	2.074128	0.383368
t2124TRUE	0.406406	1.412651	2.05059	2.240765
Observations (N)	72,894	69,890	73,463	74,333
R Squared Marginal	0.10818996	0.09658898	0.0959443	0.0955247
R Squared Conditional	0.134304	0.1170792	0.1362842	0.133303

Note: Z-score exceeding |1.96| indicates a confidence interval of 95%. Bolded font indicates that the variable is statistically significant for all four weeks.

c. *Separate city analysis for one week of data*

We additionally report the results of separate OLS models for each city taken for the week of September 15th to 21st. Using a single week as a subset helps decrease the chance that the model variables are statistically significant due to (a) dependent observations (e.g. a user making the same trip each day) and (b) the large sample size – although the number of observations for Los Angeles and D.C. in particular is still rather high.

Table 22: Regression Results of Trip Duration for Separate Cities

	Dependent variable:					
	Log(Duration in minutes)					
	(1) LA	(2) DC	(3) CHI	(4) NYC	(5) DET	(6) LOU
Gross residential density (HU/acre)	-0.002***	-0.001***	-0.007***	0.001	-0.006***	-0.004
	(0.0004)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.005)
Housing and Employment Entropy	0.083***	-0.018	-0.052	0.072	0.081	0.068
	(0.026)	(0.026)	(0.045)	(0.056)	(0.057)	(0.097)
Working age population within 45 minutes auto travel time (in 1000s)	-0.0003***	-0.002***	-0.001***	0.001***	-0.001**	-0.011***
	(0.00003)	(0.0002)	(0.0003)	(0.0001)	(0.001)	(0.002)
Distance from population weighted centroid to nearest transit stop (meters)	0.000001***	-0.000001	-0.0002**	-0.000002***	0.00001***	0.0002
	(0.0000002)	(0.000001)	(0.0001)	(0.0000006)	(0.000002)	(0.0002)

Aggregate frequency of transit service within 0.25 mi of CBG per hour	-0.00002***	0.0002***	0.0004***	0.0003	-0.001***	Omitted[7]
	(0.00001)	(0.00001)	(0.0001)	(0.0002)	(0.0001)	
Total road network density	0.007***	0.005***	0.0003	-0.006***	0.005***	-0.003*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Percentage of CBG with two or more cars	0.0004	-0.002***	0.001	0.001	-0.0002	-0.001
	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)
Trip ends within 0.1 mile of fixed transit	-0.093***	-0.059***	-0.055*	-0.048	NA	NA
	(0.023)	(0.012)	(0.030)	(0.036)		
Trip ends inside a park	0.315***	0.104***	0.122**	0.255***	0.065**	0.146
	(0.030)	(0.014)	(0.053)	(0.067)	(0.029)	(0.109)
Percentage of CBG aged 18-21	-0.002***	-0.0002	-0.009***	0.004	-0.005***	-0.005***
	(0.001)	(0.0003)	(0.001)	(0.004)	(0.001)	(0.001)
High % of minority	0.013	0.052***	0.044	0.056*	0.111***	0.099***
	(0.011)	(0.011)	(0.031)	(0.029)	(0.039)	(0.035)
High % of under poverty rate	0.027**	0.032***	0.078***	-0.091***	0.013	-0.050
	(0.011)	(0.009)	(0.024)	(0.029)	(0.028)	(0.040)
Is a scooter (Alternative is a bike)	-0.271***	NA	NA	NA	NA	NA
	(0.011)					
Daily Temperature	-0.003	-0.003***	0.021***	0.010***	0.013***	-0.015
	(0.007)	(0.001)	(0.007)	(0.003)	(0.004)	(0.010)
Daily Precipitation	NA	NA	-0.020	NA	-0.318	NA
			(0.085)		(0.296)	
Daily Windspeed	0.009	0.002	0.005	0.006	-0.003	0.022**
	(0.009)	(0.002)	(0.010)	(0.011)	(0.007)	(0.011)
Is during Weekend	0.121***	0.188***	0.012	0.101***	0.343***	0.188***
	(0.011)	(0.009)	(0.051)	(0.030)	(0.017)	(0.025)
t03	-0.087***	0.048*	NA	-0.174***	0.267***	-0.217
	(0.022)	(0.025)		(0.058)	(0.039)	(0.367)
t36	-0.211***	-0.143***	NA	-0.414***	0.407***	NA
	(0.037)	(0.042)		(0.074)	(0.076)	

[7] Variable omitted due to high Variance Inflation Factor (VIF)

t69	-0.241***	-0.373***	-0.217***	-0.381***	-0.473***	-0.392***
	(0.018)	(0.017)	(0.034)	(0.043)	(0.029)	(0.050)
t912	-0.136***	-0.159***	-0.132***	-0.160***	-0.317***	-0.154***
	(0.015)	(0.013)	(0.028)	(0.042)	(0.027)	(0.035)
t1215	-0.068***	-0.047***	-0.073***	0.018	-0.056***	-0.101***
	(0.014)	(0.011)	(0.024)	(0.038)	(0.022)	(0.030)
t1821	-0.008	-0.020*	0.018	0.018	0.064***	0.139***
	(0.013)	(0.011)	(0.023)	(0.036)	(0.021)	(0.030)
t2124	-0.109***	0.024	0.281***	-0.033	0.253***	0.613***
	(0.017)	(0.015)	(0.043)	(0.044)	(0.026)	(0.073)
Constant	6.829***	7.297***	5.623***	5.533***	5.903***	9.251***
	(0.498)	(0.107)	(0.592)	(0.234)	(0.326)	(0.839)
Observations	22,478	31,367	5,067	3,427	8,452	3,537
R^2	0.106	0.119	0.063	0.095	0.199	0.152
Adjusted R^2	0.105	0.118	0.059	0.089	0.197	0.147
Residual Std. Error	0.653 (df = 22454)	0.673 (df = 31344)	0.599 (df = 5045)	0.676 (df = 3404)	0.645 (df = 8429)	0.633 (df = 3517)
F Statistic	115.369*** (df = 23; 22454)	192.363*** (df = 22; 31344)	16.213*** (df = 21; 5045)	16.215*** (df = 22; 3404)	95.481*** (df = 22; 8429)	33.198*** (df = 19; 3517)
Note:	Number in parenthesis represents the standard error *p<0.1; **p<0.05; ***p<0.01					

d. Definitions of High Poverty Rate and High Minority Percentage for Duration Models

We define Poverty Rate and Minority Percentage as dummy variables in the model because continuous variables had a high VIF (>5) for one of the cities and an alternative to omission was needed since the variables are important to the question of equity. Both dummy variables are considered "high" if they are above the 50% average for their respective city. For instance, 50% of Louisville's CBGs have at least

24.4% minorities and 50% of Detroit's CBGs have at least 88.9% minorities. Below is a table of the threshold for each city:

Table 23: Definition of Dummy Socio-economic and demographic variables

	LA	DC	CHI	NYC	DET	LOU
50^{th} percentile for Minority	39.1	35.9	75.8	52.4	88.9	24.4
50^{th} percentile for Poverty Rate	15.5	8.2	18.5	11.9	35.5	19.5

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